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INFORMATION AGGREGATION IN EXPERIMENTAL ASSET MARKETS: TRAPS AND MISALIGNED BELIEFS

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Information Aggregation in Experimental Asset Markets: Traps and Misaligned Beliefs*

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Abstract

The capacity of markets to aggregate information has been conclusively demonstrated but the limitations of that capacity have still not been fully explored. In this paper, we demonstrate the existence of "information traps". These traps appear to be a sort of equilibrium in which information existing in the market does not become revealed in prices. The foundation for the equilibrium is a pattern of misaligned beliefs in which each person's actions are based upon mistaken beliefs about the information held by others. The mistakes, themselves, have a type of mutual compatibility and cannot become revealed by the price discovery process because individuals have no incentives or resources to adjust. Attempts to probe the nature of the phenomena involved two period markets with a contingent claim instrument, experienced participants, and unlimited short selling opportunities.

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Consider the following situation in which three pieces of information exist in a market: Some participants know the short term payment of a stock, i.e. the next quarter's dividend. The other participants have partial information on the future stock price in six months. For example, some have perfect information that the stock price will not drop below the current level and others know that the stock price will not be at the current level. The combination of their information result in a perfect forecast of this stock price, i.e. the stock price will go up.[1] Asset markets like the New York Stock Exchange or NASDAQ are believed to aggregate this type of distributed information quite well, if not perfectly. Moreover, the capacity of (experimental) markets to aggregate information has been conclusively demonstrated although the limitations of that capacity have still not been fully explored.

In this paper, however, we report on the discovery of a special type of phenomenon (*information trap*) that can exist in markets with asymmetric information of the type described above. These traps appear to be a sort of equilibrium in which information existing in the market does not become revealed in prices. The foundation for the equilibrium is a pattern of *misaligned beliefs* in which each person's actions are based upon mistaken beliefs about the information held by others. The mistakes, themselves, have a type of mutual compatibility and thus cannot become revealed by the price discovery process.

The nature of information aggregation in experimental markets is of interest for two reasons. The first interest stems from an opportunity to extend a very powerful theory, i.e. Rational Expectations. The information structure, i.e. the amount and the specific distribution of information, is known at every second within an experiment. Therefore, it is possible to explore dimensions of theories in finer detail than one can do using naturally-occurring data. As a result, it is possible for us to document unusual patterns that can only be guessed at using naturally-occurring data. For example, one of our main contributions is to establish that in some periods, feedback from prices leads to information traps in which one group of traders ends up believing that the assets have a value which another group of traders knows cannot possibly be the true value. This may strike some readers as impossible, but keep in mind that our experiments enable us to see patterns in beliefs and prices that are usually not visible in naturally-occurring markets. It may be that these sorts of conflicting beliefs are very common in naturally-occurring markets, but usual sources of data disguise their existence. Experiments therefore provide a kind of x-ray or special insight into detailed microstructure which, of course, should be used to form conjectures that can be later tested using naturally-occurring data. In addition, one can vary the specific variables in order to isolate certain factors which might influence the process of information aggregation.

Experiments are a legitimate test of general theories like the efficient markets hypothesis because those theories should apply to simple, artificially-created markets (like those in this experiment). That is, such theories do not explicitly exclude experimental tests as an area of application. According to the general theory, the phenomena we report should not occur in any market, so the first step is to document their existence. The second step is to help the theorists by attempting to isolate both the mechanism that

[1]This scenario includes various assumptions. For example, all participants know that their private information is always correct and the complete payment structure is common knowledge. However, this very simple example is sufficient to understand the intuition of our experimental design.

seems to bring it about and by developing measurements and indicators that might help with a search to determine if it can be detected in the more complex, naturally-occurring markets. The growing literature on the possible impact of individual mistakes in assessing private information[2] demonstrates the necessity of paying more attention to the *process* of information aggregation. In addition, our data put the burden of proof on those who have faith in the general hypothesis to explain why the same phenomena would *not* occur in naturally-occurring markets. Critics who think experiments are unrealistic or unfair tests of general hypotheses should articulate the conditions under which experiments would represent fair tests.

The second source of interest stems from a long history in experimental economics, investigating whether or not the information held by the insiders will necessarily emerge from the market activity and be reflected in the market prices. Although information aggregation could be observed in general there are several difficulties which might prevent or slow down information aggregation. Information aggregation within *one* period could be observed in the experiment of Plott and Sunder (1982) with dividend payments dependent on two states and three trader types which differed only on the paid dividends associated with the states. However, extending this design to three states ruined the aggregation. Plott and Sunder (1988) demonstrated that a complete set of Arrow/Debreu securities helped to achieve aggregation in this setting. Aggregation also occurred with three possible states and common dividends even without these securities. Copeland and Friedman (1987, 1991, 1992) analyzed the impact of information arrival within one period. They found that it takes the market some time to partially aggregate the newly arrived information.

Forsythe, Palfrey and Plott (1982) studied information aggregation in markets in which securities with a *two-period* life were traded. Each participant knew at the beginning of a two-period market how much money she would earn without trading. But since there existed two different trader types who received different dividends at the end of both periods, subjects had an incentive to trade to earn more money. In this experiment, information aggregation was observable, too. O'Brien and Srivastava (1991) used a fairly complicated design with three or even four independent securities traded at the same time over two periods. In addition, they tested the limits of information aggregation even more by introducing up to six possible states. In most cases, these markets were not able to aggregate this very complex information. Forsythe and Lundholm (1991) found that both trading experience and common knowledge of dividends were only jointly sufficient to achieve a RE equilibrium.[3]

Although these results suggest that information aggregation in simple markets is possible, there are indications that market participants are not always able to infer others' information via market prices. Information aggregation consists of the correct reflection of all available information, i.e. aggregation is not achieved if information is either not completely or not correctly reflected in prices. For example, Camerer and Weigelt (1991) show that even in situations without any information, trading patterns are sometimes similar to those with private information just because some investors believe that others have private information. Thus, it is not necessary that some investors have private information to move asset

[2]See for example Daniel, Hirshleifer and Subrahmanyam 1998.

[3]Schnitzlein (1996), Lamoureux and Schnitzlein (1997), Bloomfield (1996) as well as Bloomfield and O'Hara (1998, 1999) use a different market structure and a different information structure to evaluate market micro structure models.

prices. In addition, Sunder (1992) reports that with just one to three traders price converge to the wrong price, i.e. "prices were close to the F[ull] R[evelation] price for state x when, in fact, the realized state was y" (p. 690). Forsythe and Lundholm (1991) find convergence to the price and allocation of a wrong state, too. They describe the specific reasoning of all traders after an individual "mistake" of trader 11 in period 9. The information of the "Not Y"-informed participants never became incorporated in prices since they had an incentive to sell as many securities as possible at inflated prices. As a result, prices and allocations converged to the "Y"-state scenario (see p. 339). In those cases in which the number of insiders were uncertain, Nöth and Weber (1996) found trading patterns which are similar to the information mirages. In addition, a monopolistic insider tried to manipulate the market by trading against her private information for some time before she attempted to offset her losses later. This behavior was not profitable but demonstrated the possibility that individual behavior might destroy information aggregation.

DeLong, Shleifer, Summers and Waldmann (1991) even showed that noise traders without any strategic considerations can survive under certain circumstances because of the risk they create for "rational" traders and the resulting risk premium. Daniel, Hirshleifer and Subrahmanyam (1998) explain many "anomalous" stock price movements by introducing overconfident market participants who underestimate the variance of their individual signal. These two papers demonstrate that robust psychological findings can be incorporated into financial theory to understand stock price movements and the process of information aggregation.[4]

The growing literature on (rational) herd behavior [5] shows that even with fully rational agents or traders aggregation might not be achieved. In these models prices and/or allocations deviate from the RE equilibrium because agents base their individual decisions not only on their own private information but also on the observed behavior of other agents. Under special circumstances this fully rational behavior leads to a situation in which agents neglect completely their private information and follow the crowd. The result is an inefficient allocation of resources and mispricing. Notice, that the inefficient outcome is not the result of false assumptions about the knowledge and beliefs of traders who acted earlier concerning their information. In these models herd behavior results because of the specific information structure and incentives for the agents. And the exogenous ordering of decisions can contribute to the inefficiency, as Gul and Lundholm (1995) point out. They demonstrate that clustered decisions are not necessarily an indicator of herd behavior. Instead, clustering can be the result of endogenous timing of agents' (rational) decisions using all available information. Moreover, Gul and Lundholm show that endogenous timing, i.e. the choice to act first or wait until other agents act, conveys information and thus has an influence on information aggregation.

Summing up, markets do indeed have the capacity to aggregate information. However, such capacity is not perfect and neither the circumstances under which the aggregation might occur nor the processes that

[4] Hong and Stein (1999) have two types of traders in their model which do not use all available information and which are restricted to implement only simple strategies by assumption. As a result the existence of over- and underreaction can be explained.

[5] See for example Scharfstein and Stein (1990), Froot, Scharfstein and Stein (1992) and Bikhchandani, Hirshleifer and Welch (1992) as early examples, as well as Anderson and Holt (1997) for the first experimental study of information cascades.

lead to the aggregation are well known. It is known however that the existence of special and additional certificates, such as a complete set of Arrow/Debreu securities as used by Plott and Sunder (1988), add substantial power to the process of information aggregation.[6]

The research reported here began with a project that extended the traditional investigations to cases with an increased number of states and a more complex time dimension. In our experiment the common value dividend design with three possible states of Plott and Sunder (1988) is combined with the two-period information aggregation feature studied by Forsythe, Palfrey and Plott (1982) resulting in six possible states in the first period and a replication of Plott and Sunder (1988) in the second period. This information structure captures a situation in which some investors know the next quarter's dividend with certainty whereas other investors can only rule out whether the stock price will rise, fall or stay at the current level within the next year. Initially, this research project was designed to explore the consequences of different incentives on information aggregation. The misaligned beliefs and information trap phenomena, documented and reported here, were discovered very early in the research program and resulted in a need to explore its nature before going further to manipulate the individuals' acquisition of information before trading starts by adding specific incentives.

In order to analyze these phenomena, it is necessary to have at least two dividend payments (= two trading periods) for several reasons. First of all, this design allows us to ask subjects twice about their beliefs just before the dividend is announced and compare both results contingent on the first period dividend, i.e. to observe the updating process in addition to transaction prices. Secondly, the design incorporates a second-period benchmark by using the Plott and Sunder (1988) common dividend design. If information is not aggregated in the second period the dynamics of the first period will be accountable for the formation of misaligned beliefs and information traps. Thirdly, in a two-period design traders might believe that they can unwind their position before the liquidation value is paid **and** receive payments (=dividends) for holding the asset which leads to speculation.[7]

Information traps are an example of the self-confirming equilibrium introduced by Fudenberg and Levine (1993a) in game theory. In our experiment some participants know that observed prices cannot be the equilibrium price since they can rule this but by using their private information. However, these information traps are (mostly)[8] stable because those participants who know that observed price are not correct have no incentive (assuming risk neutrality) to convince the market to move in another direction.

In this paper we ask three questions:

1. Can the existence of misaligned beliefs and information traps be detected and documented;

2. Is the existence of these phenomena robust to certain kinds of institutional changes;

[6] Sunder (1995) and Duxbury (1995) provide summaries of the literature about experimental asset markets.

[7] The bubble experiments run by Porter and Smith (1994) demonstrated that speculation can cause bubbles even with perfect knowledge about future payments.

[8] In two cases with experienced subjects information traps collapsed because some participants obviously suspected the existence of a trap and tried to sell their assets resulting in a crash.

3. What market dynamics bring these phenomena into existence.

Of course, one would like to know if the phenomena occurs frequently but it is too early to pose that type of question. This paper is confined to the study of simple experimental markets. Information aggregation and the convergence towards the RE equilibrium is observable. However, information traps due to traders' misaligned beliefs occur frequently in our special setting. Although common dividends are paid, the existence of traps is still observable even with experienced traders. The introduction of an additional state contingent claim market helps to avoid information traps but non revealing equilibria still exist.[9] Traps develop on a combination of individual misbehavior such as plunging or scalping as well as eliminating the correct state on the basis of prices and private information.

We proceed with the experimental design and procedures. In section 2 we will present information aggregation theory for this experiment as well as a definition of both, misaligned beliefs and information traps. Section 3 contains the main results. Some explanations and theoretical speculation about the development of information traps are discussed in section 4. The final section 5 is a summary of conclusions.

1. Experimental Design and Procedures

1.1 General Design

This experimental series consists of fourteen sessions. The first eight took place at the California Institute of Technology and the last six were conducted at the Universität Mannheim.[10] All of the following parameters were fully known by all participants since they were part of the instructions (see Appendix A). Each participant within one session received the same number of identical 'regular' certificates at the beginning of a trading year. These certificates have a two period (=one year) life and will pay a common dividend in both periods which last seven minutes each. The dividend paid in period A will be determined by a random choice of states H_A and L_A $\left(p_A = \frac{1}{2}\right)$ and the dividend in period B will be determined independently by a random choice of states H_B, M_B, and L_B $\left(p_B = \frac{1}{3}\right)$.

Figure 1 shows that the dividend is 100 currency units (cu) higher in period A if state H_A occurs. In period B the dividend will be 400 (200) cu higher at state $H_B, (M_B)$ than if state L_B occurs.[11]

In some sessions there are additional H_B-certificates which will pay a common dividend of 100 cu only at the end of period B if state H_B occurs and 0 cu otherwise. However, it is possible to trade these H_B-certificates in a second market throughout the whole trading year. The markets are organized as a computerized multiple unit double auction resembling a continuous market.[12]

[9] A related paper by Plott, Wit and Yang (1997) supports the notion that other market structures, e.g. a betting market, have an important or even decisive impact on the capability of markets to aggregate dispersed information.

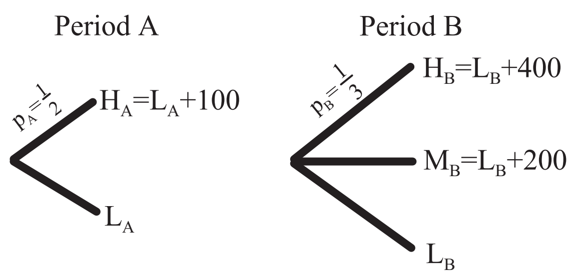
[10] We translated the set of instructions to make sure that the language did not cause different behavior in Germany.

[11] We had to change the L_A and L_B dividends since we used the time series of draws more than once to compare the price process across sessions.

[12] For a detailed description of the Multiple Unit Double Auction (MUDA) software, see Plott (1991).

Figure 1: Dividend structure

Assets in this experimental market have a two-period life. After period A assets pay a dividend of either L_A or $H_A = L_A+100$. At the end of period b the liquidation value is with probability $p = \frac{1}{3}$ either high ($H_B = L_B+400$), medium ($M_B = L_B+200$) or low (L_B). All payments are in currency units which are converted into US$ or DM at the end of the experiment.



At the beginning of every year each subject gets ten *regular* certificates and ten H_B-certificates if they exist.[13] The inventory of certificates and cash is carried over from period A to period B. Subjects receive no cash endowment but there is no restriction on lending money, which has to be paid back with no interest at the end of each year. In addition, subjects must pay the minimum dividend ($L_A + L_B$) for each *regular* certificate. Except for sessions 9512111, 9512112 and 9512121 participants are not allowed to sell certificates short. Table 1 summarizes the relevant parameters for all sessions.

1.2 Information Structure

The states are drawn and are known to the experimenter before any market periods are started. Before the opening of a market period A, information is randomly distributed to all participants, i.e. information about the state in period A and period B is distributed before the market opens for period A. One third of the participants are given complete private information about the dividend that will be paid at the end of period A. The remaining two thirds of the subjects who do not have private information about the period A dividend receive information about the states that will NOT occur in period B.[14] Since half of the period B informed participants will be able to eliminate one state and the other half can eliminnate the other, collectively their private information would allow them to identify with certainty the period B dividend that will be paid.

Subjects know that all private information is correct in all cases. Note that four (in sessions with twelve traders) or five (fifteen traders) participants receive the same information and have no opportunity to communicate with each other except via limit or market orders. Thus, they cannot cooperate and act strategically to hide their information etc. Moreover, subjects cannot choose whether they would like to get information about period A or period B because they have to draw an information card out of a box.[15]

[13] In session 9510281 subjects receive just five *regular* certificates.

[14] Foster and Viswanathan (1996) demonstrate with their model that the information structure, i.e. the intial correlation among the informed traders' signal, has a significant effect on the informed traders' profits and the information conten of prices.

[15] This procedure makes sure that subjects cannot specialize on any specific type of information.

Table 1: Design: Main Parameters

In this table the most important parameters are displayed for each session of this experiment. The sessions took place either at the **C**alifornia Institute of Technology or at Universität **M**annheim. The next column shows the number of traders (*no. T*). Traders were either inexperienced (*exp.*= no) or they participated once before in the same experimental setting (*exp.*= yes). The number of trading years in which dividends could be earned is displayed in the next column (*no. Y*). The common dividend payment (in currency units) is shown for each certificate depending on the state in period A and B. # *C* and $\#H_B$ are initial endowments (per subject) of regular certificates and H_B-claims, respectively. *Short* selling restrictions (*yes / no*) existed in most sessions. Except for one session (9510281), participants had to place one of two *bets* on the RE price (*: in session (9511041) existed just one bet).

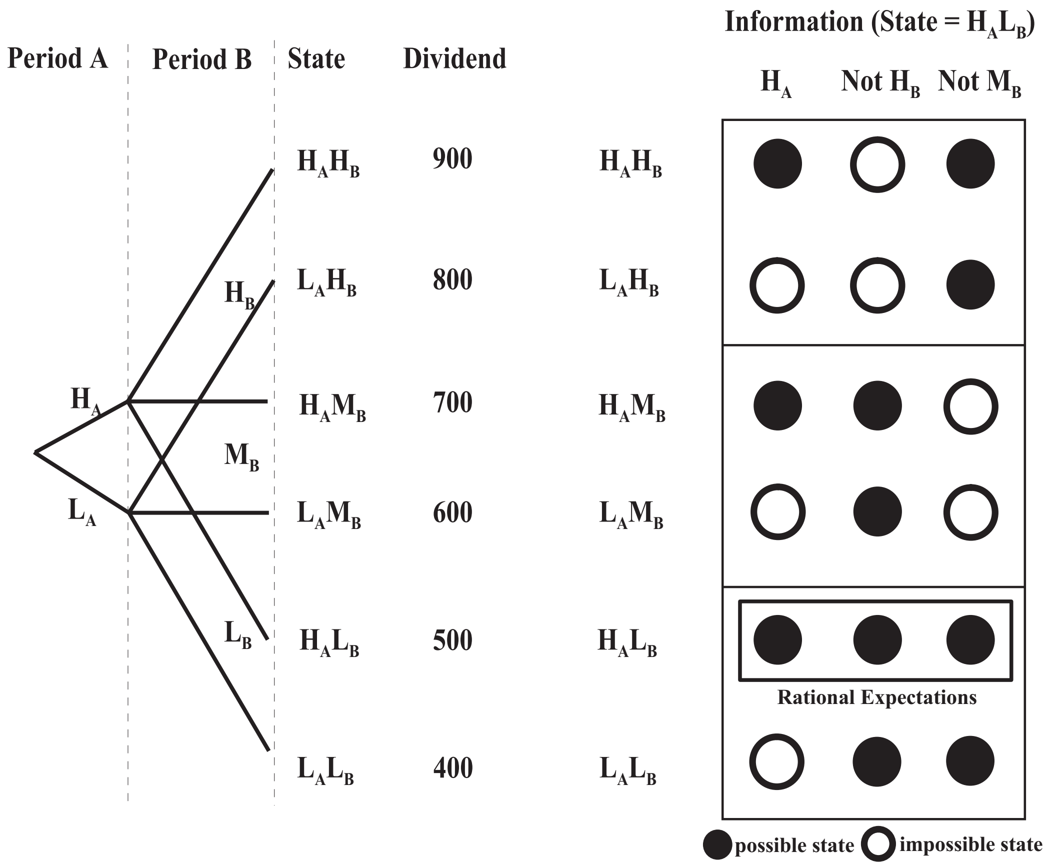
					Period A		Period B			Certificates			
Session	Place	# P	exp.	# Y	H_A	L_A	H_B	M_B	L_B	# C	# H_B	Short	Bets
9510281	C	12	no	9	200	100	500	300	100	5	NA	no	no
9511041	C	12	no	9	300	200	600	400	200	10	NA	no	yes*
9511091	C	15	no	8	300	200	600	400	200	10	NA	no	yes
9511141	C	15	no	8	300	200	500	300	100	10	NA	no	yes
9511161	C	15	no	8	200	100	600	400	200	10	NA	no	yes
9511261	C	15	yes	10	200	100	600	400	200	10	NA	no	yes
9511271	C	15	yes	10	200	100	600	400	200	10	NA	no	yes
9511281	C	15	no	8	200	100	600	400	200	10	10	no	yes
9512111	M	10	no	9	200	100	400	NA	100	10	NA	yes	yes
9512112	M	10	no	9	200	100	400	NA	100	10	NA	yes	yes
9512121	M	12	no	8	200	100	500	300	100	10	NA	yes	yes
9512131	M	12	no	8	300	200	600	400	200	10	NA	no	yes
9512141	M	12	no	7	200	100	600	400	200	10	NA	no	yes
9512151	M	12	no	7	200	100	500	300	100	10	NA	no	yes

The following example will clarify the information structure: If state H_AL_B occurs one third of the participants receive private information before the period A market(s) open that state H_A will occur and thus they will receive the dividend $H_A = L_A + 100cu$. Another third of the traders knows from their private information that they will not get the state H_B dividend ($H_B = L_B + 400cu$) at the end of period B. The remaining third of the participants can exclude state M_B for period B. As a result, all participants together (=the market) know at the beginning of period A that the state is H_AL_B. Accordingly, the value of the 'regular' certificate in period A is equal to the sum of dividends D_A^H and D_B^L and it is equal to dividend L_B in period B.[16] Figure 2 clarifies the information structure for this example. Note that there is only one Rational Expectations Equilibrium but three cases in which two of the three information groups can agree on a state, i.e. H_AH_B ($H_A$and$NOTM_B$informed groups), H_AM_B ($H_A, NOTH_B$) and L_AL_B ($NOTH_B, NOTM_B$).

[16]Plott, Wit and Yang (1997) used the same information structure as in this experiment but paid a dividend which depended on the total betting amount.

Figure 2: Information structure: state = $H_A L_B$

For each state combination exists a well-defined equilibrium based on the combination of dividend payment and liquidation value. Note, that the potential equilibrium prices are at least 100cu apart to ensure a clear distinction between different state combinations. The combination of all available information always implies only one state combination.



There are some differences in sessions 9512111 and 9512112 in which only state H_B or L_B can occur in period B (dividend difference 300cu). Participants receive either information on the state of period A or on that of period B, i.e. some subjects know exactly the dividend of period B. After year 4 subjects can choose whether they would like to receive information on period A or on period B. The number of participants who chose A is announced at the end of period B. These two sessions serve as a benchmark for the other sessions since the information and dividend structure is simpler: Information aggregation is achieved even in the first trading year.

1.3 Bets on the Dividends

Transaction prices typically reflect the average opinion of all market participants about the value of the certificates. However, it is possible that some traders have a different opinion but they cannot or do not want to trade. In addition, just one buyer and one seller participate in a specific trade and the other traders are just observing the transaction price. Because we cannot infer traders' beliefs based only on transaction prices, we asked all subjects at the end of each period to predict all future dividend(s) of the 'regular' certificates in this year, i.e. at the end of period A they predicted the sum of dividends for both periods. The predictions are collected before the period's dividend is announced.

In order to get more reliable predictions, subjects have to place one of two possible bets on their prediction (see Grether, 1992).[17] Choosing a specific bet reveals to some extent the certainty which is assigned to the prediction. The bets are constructed as follows. Bet I will result in a payment of US\$ h_1 (US\$ l_1) if the prediction is correct (wrong). Bet II is defined accordingly. Under the assumption of risk neutrality a subject will be indifferent between both bets if the probability p_i of the predicted state satisfies $p_i * h_1 + (1 - p_i) * l_1 = p_i * h_2 + (1 - p_i) * l_2$. As a result, subjects will prefer bet I if $p_i > \frac{l_2 - l_1}{(h_1 - l_1)(h_2 - l_2)}$. Since we choose $h_1 > h_2$ and $l_1 < l_2$ subjects will prefer bet I over bet II if they have a higher degree of certainty concerning their prediction. Note that we do not have any specific information about individual's probability distribution since we only asked for a point estimate.

Let us assume that you are in one of the CalTech sessions at the end of period A and must predict the sum of dividends for both, period A and period B. With information on the period A (B) dividend you can rule out three (four) of the six possible states. Bet I will pay US\$0.60 (US\$-0.30) if your prediction is correct (wrong). If you choose bet II you will receive US\$ 0.30 with a correct prediction and you will lose US\$ -0.10 otherwise. As a result you will take bet II only if you assign to your prediction a probability of being correct of at least 0.40. Choosing bet I at the end of period A signals that a participant is certain of having at least two thirds of the available information. Table 7 (in Appendix B.) provides data about the design of bets for all experiments.[18]

After reading the instructions subjects get accustomed to the procedure (information distribution, trading, and betting on their own prediction) by participating in a trading year without getting paid. Figure 3 provides a time line illustrating all relevant aspects of the design and of conducting the experiment.

1.4 Subject Pools

In sessions at the California Institute of Technology twelve or fifteen subjects participated whereas at Universität Mannheim just twelve students participated in a session. All 84 subjects at the California Institute of Technology have prior experience with experiments because they are recruited by e-mail out of a subject pool of former participants. Some subjects of sessions 1-5 participated again in sessions 6 and 7, i.e. they have experience in this specific experiment. The 68 subjects in Germany are primarily recruited from graduate courses in banking and in finance. Those students who have never participated before, receive a mandatory training lesson of about 45 minutes to learn how to handle the trading software MUDA.[19]

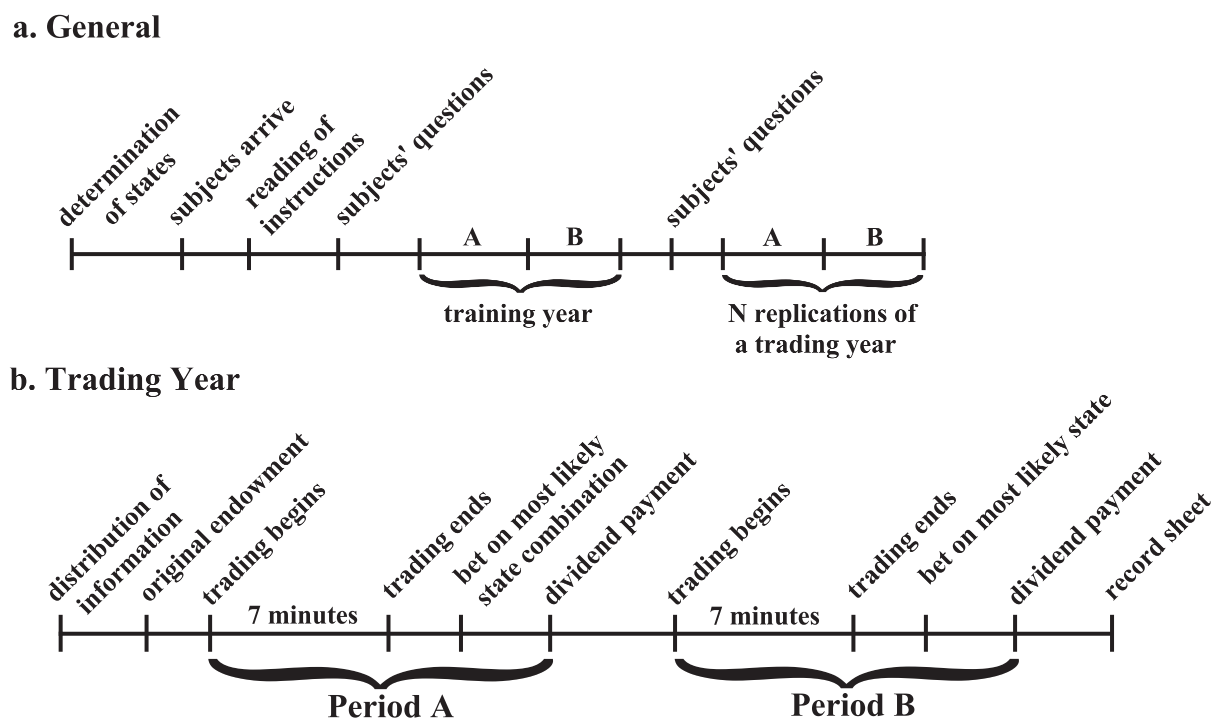
[17] In session 1 no predictions are collected. In session 2 participants receive US\$ 0.50 for a correct prediction and have to pay US\$ 0.25 otherwise.

[18] In the sessions conducted in Mannheim we increased the p_i value to obtain a clearer signal if a subject with an information about the first period chooses the high bet. For the two sessions with just two possible states in period B we had to adjust the bets due to the information structure.

[19] In these training sessions they get no information about the parameters of the real experiment.

Figure 3: Timeline of this experiment

In part a) of this figure the general timeline for this experiment is displayed. Part b) shows the specific procedure with one of the trading years. Note that all information is distributed before trading in period A starts.



2. Definitions, Models and Information Aggregation Process

Participants have an incentive to trade in this experiment since they receive private information at the beginning of a trading year. The resulting differences in expected values start the trading process as participants adjust their positions. Then, trading continues as market participants update their beliefs. In addition, the two period design opens some room for trade-based and information-based speculation. For example, overconfident subjects overestimate the information they observe from transaction prices and thus speculate (=bet) rather early on a specific state. $NOTM_B$-informed participants who know that certificates will either pay a high (H_B) or a low (L_B) period B dividend may be especially tempted to bet early whether H_B or L_B will occur and thereby influence prices and other traders' beliefs.

Observed transaction prices and beliefs will be compared to three benchmarks. Based on these comparisons we will be able to search for and analyze trading patterns which lead to systematic nonaggregation which we will call information traps.

2.1 Rational Expectations

Under Rational Expectations all information will finally become incorporated in prices.[20] There is no allocation prediction since everyone knows (at the end) which dividend(s) will be paid. Regardless of the

[20]It is an experimentally well established result that it takes some time to reach an RE equilibrium. See for example Forsythe and Lundholm (1990).

private information every trader received at the beginning there should exist a common belief about the true state at the end of a trading period or year.[21]

2.2 Random Choice Model (Private Information)

Our second benchmark concerning beliefs is based on each individual's private information. The prior or private information (PI) model predicts that those traders with the highest expected value will hold all certificates at the end of each period, e.g. $NOTL_B$-informed will always buy all certificates up to their expected value (period A: halfway between $H_A + M_B$ and $L_A + H_B$; period B: halfway between M_B and H_B) if states H_B or M_B occur. Traders cannot learn anything from transaction prices within this model.

The individual beliefs provide further evidence whether subjects have learned anything about others' information. No learning would lead to a situation in which Period A informed subjects can rule out three out of six possible states in period A with their private information and none of the three states in period B. Period B informed participants can eliminate two states in period A and one state in period B. Under the assumption that all subjects guess randomly based only on their private information (Random Choice Model: RCM) we can derive a new benchmark distribution as demonstrated in table 2 for state H_AL_B:

Table 2: State H_AL_B: Random Choice Model vs. Rational Expectations

The distribution of predictions for each information group in state H_AL_B is shown in this table based only on private information. Assuming equal size of all information groups, the Random Choice Model (RCM) combines the random guesses of all groups. Without any information in the market, the random distribution of predictions would look like those in row *no info*. If all available information is aggregated (*RE*) all participants should predict the correct state H_AL_B.

	Period A						**Period B**		
information	H_AH_B	H_AM_B	H_AL_B	L_AH_B	L_AM_B	L_AL_B	H_B	M_B	L_B
H_A	$\frac{1}{3}$	$\frac{1}{3}$	$\frac{1}{3}$	0	0	0	$\frac{1}{3}$	$\frac{1}{3}$	$\frac{1}{3}$
$NOTH_B$	0	$\frac{1}{4}$	$\frac{1}{4}$	0	$\frac{1}{4}$	$\frac{1}{4}$	0	$\frac{1}{2}$	$\frac{1}{2}$
$NOTM_B$	$\frac{1}{4}$	0	$\frac{1}{4}$	$\frac{1}{4}$	0	$\frac{1}{4}$	$\frac{1}{2}$	0	$\frac{1}{2}$
RCM	$\frac{7}{36}$	$\frac{7}{36}$	$\frac{10}{36}$	$\frac{3}{36}$	$\frac{3}{36}$	$\frac{6}{36}$	$\frac{5}{18}$	$\frac{5}{18}$	$\frac{8}{18}$
no info	$\frac{1}{6}$	$\frac{1}{6}$	$\frac{1}{6}$	$\frac{1}{6}$	$\frac{1}{6}$	$\frac{1}{6}$	$\frac{1}{3}$	$\frac{1}{3}$	$\frac{1}{3}$
RE	0	0	1	0	0	0	0	0	1

Since all information groups have the same number of members it is easy to compute the RCM value as the mean of random guesses for each state. Notice the peaks of $\frac{10}{36}$ and $\frac{8}{18}$ at the correct state H_AL_B and L_B in period A and period B, respectively. In addition, table 2 displays the 'no information value', i.e. the proportion of random guesses without usage of any private information, and the distribution of guesses

[21] Market participants' risk attitude might have an influence on how close observed prices are to the fundamental value. However, there is no reason why risk attitude should be state dependent and thus it will not influence the outcome considerably. In addition, previous experiments have shown that subjects are on average almost risk neutral in this type of experiment.

under the RE assumption. The aggregation of all guesses only provides a first hint whether the available information is aggregated by market participants or not. In order to differentiate between systematic and unsystematic nonaggregation of information we need a clear concept and measure to classify each period's aggregation result.

2.3 Misaligned Beliefs

In this subsection we will introduce the concept of misaligned beliefs which is the basis for systematic misaggregation, i.e. information traps. Misaligned beliefs are always the result of individual mistakes interpreting private information or price movements (see section 2.6). Since traders cannot always observe or detect these individual mistakes they interpret the noisy price signals as if they are based on fully rational behavior. As a consequence (pseudo-rational) herd behavior and the development of misaligned beliefs can influence prices significantly. In this context we define misaligned beliefs:

Definition:*Misaligned beliefs* consist of a consensus within information groups and a systematic lack of consensus between information groups.

Each trader can be classified by her private information as a member of a specific *information group*. Within our design there are three information groups defined by the initial distribution of private information. For example, if state H_AL_B occurs, the information groups $I\,(H_A)$, $I\,(NOTH_B)$ and $I\,(NOTM_B)$ exist. If members of an information group have the same beliefs about the certificates' fundamental value and these beliefs differ from each other we have a *systematic lack of consensus*. For example, at the beginning of a trading year there is consensus within each information group but due to different private information there is no consensus between the groups. This consensus which is in this experiment only achievable at the REE can only be reached by updating based on either market transactions or based on observable offers (bids & asks).

Note, that the definition of misaligned beliefs do not incorporate any dynamic feature of their evolution and stability. Beliefs might change based on public information. Whether this change leads to different misaligned beliefs or to the RE equilibrium depends on the interpretation of price movements. These different interpretation can influence for example the timing decisions by traders: Overconfident subjects will choose to trade early based on their own private information and on their incorrect estimation of the certificates' true value. Other traders who behave fully rational and who cannot differentiate between rational and "overconfident" prices now learn distorted information and thus form ex-ante correct but ex-post incorrect beliefs. This process can stabilize or even increase the mispricing and lead again to *misaligned beliefs*. As a result, prices cannot be at the RE equilibrium.

The general definition of Misaligned Beliefs can be stated more precisely using a special feature of our design. The special definition eliminates all situations in which all three information groups have different consensus beliefs. Instead we require that two information groups have a single consensus which is different from that of the remaining group. Combined with the prediction of the most likely state (combination), this implies that both newly formed groups know that the belief of the other group is not possible based on the own private information. Take state H_AL_B again as an example. Suppose groups $I\,(H_A)$ and $II\,(NOTM_B)$ have the consensus belief that state H_AH_B will occur and group $III\,(NOTH_B)$ believes state H_AM_B will occur. It is obvious that both consensus beliefs are mutually inconsistent and each group knows that the other consensus belief is wrong.[22] This situation can only stabilize due to the fact that beliefs are not publicly observable.

This leads to the special definition which will be used (and relaxed) for the analysis in section 3:

Definition: *Misaligned beliefs* consist of a systematic lack of consensus between two information groups of which one group knows to be false what the other group thinks is true.

If one thinks of misalignment as differences in probability judgments of states, this means that the misalignments we observe are as large as statistically possible. In naturally-occurring settings these misalignments might of course be smaller. Nevertheless, observations derived within our setting can be used to evaluate more general situations as in naturally-occurring markets.

2.4 Mean Absolute Deviation of Beliefs

To test if participants' predictions are all in line with Rational Expectations is fairly easy by using a binomial test. However, we would like to find a measure to gain insight into the degree of deviation from both, RE and RCM. The measure should take into account not only the correct and false predictions but also the distribution of wrong predictions at the end of a period because this distribution may contain additional information about information groups' degree of learning. A very simple measure is the mean absolute deviation of beliefs which compares the relative frequencies of participants' predictions with those of a benchmark model for all possible state predictions. For comparability, the mean absolute deviation of beliefs (W_{RE}) will always be computed compared to Rational Expectations:

$$W_{RE} = \frac{1}{2} * \sum_{\text{all states}} \left| p_{RE} - p_{beliefs} \right| .$$

p_{RE}^{state} denotes the probability with which this state should be predicted under the RE assumption. It is equal to one for the correct state and zero otherwise. $p_{beliefs}^{state}$ denotes the actually observed frequency of stated beliefs for this particular state within a specific group of subjects. The mean absolute deviation of beliefs can be computed both, for all subjects as a general benchmark and for each group in order to analyze information specific learning. Misalignment of beliefs result in deviations both from RE and from RCM. Perfect misalignment leads to the maximum mean absolute deviation of beliefs of 1 for each information group. The mean absolute deviation of beliefs for the RCM model compared to RE is $W_{\text{RE}}^{\text{A}}\left(\text{RCM}_{\text{all}}\right) = \frac{1}{2} * \left(\frac{7}{36} + \frac{7}{36} + \left(1 - \frac{10}{36}\right) + \frac{3}{36} + \frac{3}{36} + \frac{6}{36}\right) = \frac{13}{18}$ in period A and $W_{\text{RE}}^{\text{B}}\left(\text{RCM}_{\text{all}}\right) = \frac{1}{2} * \left(\frac{5}{18} + \frac{5}{18} + \left(1 - \frac{8}{18}\right)\right) = \frac{5}{9}$ in period B.

Mean absolute deviation of beliefs bigger than the RCM value for an information group indicate unlearning of private information since we compute the mean absolute deviation of beliefs relative to RE.[23]

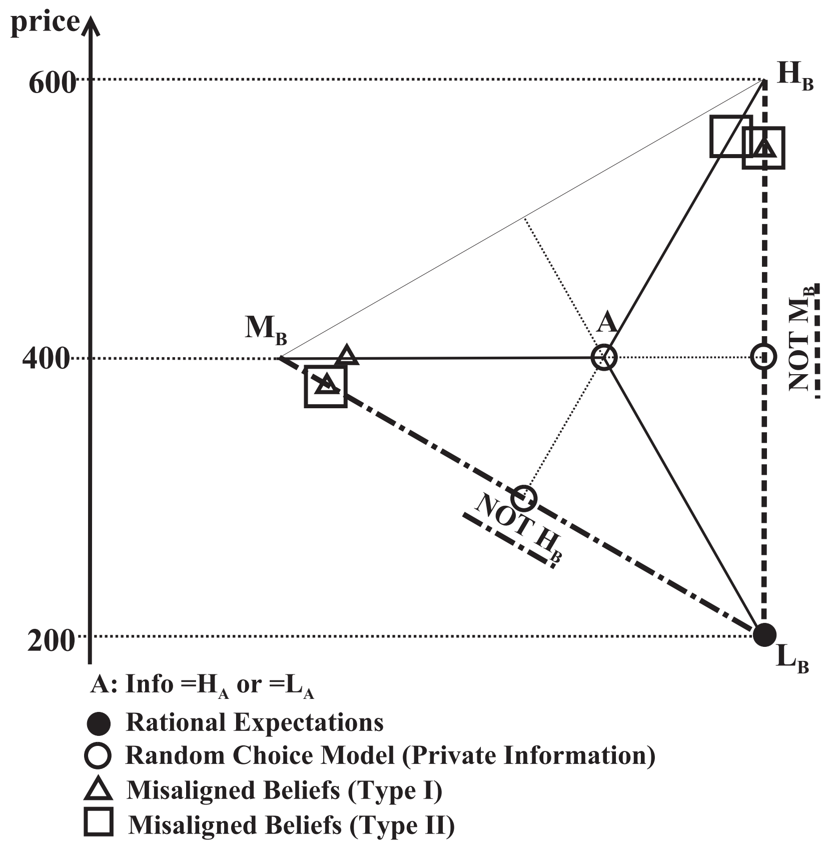
[22] Note that the crucial lack of consensus is the one between period B informed groups. It does not matter if period A informed subjects do not have a consensus within their information group.

[23] Theoretically, there exist several distribution which lead to the maximum mean absolute deviation of beliefs of 1 at the end of **period A**. All these distributions have one feature in common namely no participant predicts the correct state although this does not necessarily imply the existence of misaligned beliefs. However, at the end of **period B** the maximum mean absolute deviation of beliefs for period B informed subjects is equivalent to perfect misalignment of beliefs.

An equilateral triangle whose sides are one unit long is best suited to represent graphically the mean absolute deviation of beliefs and its' connection to prices in period B. The three states correspond to the three corners. Since period B informed subjects can rule out one state the mean absolute deviation of beliefs W_{RE} lies on the straight line between the two possible states, i.e. if all subjects of one information group predict the correct state ($W_{RE} = 0$). Halfway between the correct and the wrong state lies the RCM prediction $\left(W_{RE}^{B}\left(\mathrm{RCM}_{NOT H_B/NOT M_B}\right)\right)$ at 0.5 as can be seen in figure 4.

Figure 4: State $(H_A)\, L_B$: Triangle with mean absolute deviations of beliefs for RE, RCM and MAB

Based on the collected belief statements which include a state prediction and an associated bet on this prediction it is possible to calculate the mean absolute deviation of beliefs for all three information groups. These distances are displayed in this triangle for the beliefs of period B if state L_B occurs.



In this example for state $(H_A)\, L_B$ the filled circle at the L_B-corner corresponds to $W_{RE} = 0$, i.e. the RE prediction. The RCM predictions for each information group are plotted as circles. The period A informed participants' RCM (denoted by A) prediction lies at the same distance from each of the three corners at the center of the triangle. In principle it would be possible to put the computed mean absolute deviation of beliefs for the period A information group on any point of a circle around the RE corner and within the triangle. However, we can use data from the distribution of beliefs to specify exactly one point within the triangle. The exact location within the triangle is determined by the mode of predictions. The mark will be placed on the (solid) line from the center to the mode corner if a unique mode exists.

If two modes exist the mark will be put on the (broken) line from the triangle's center to the middle of two modes' side.

At this point we have to modify (slightly) the concept of correspondence between the mean absolute deviation of beliefs and the distances within the triangle because the distance from a corner to the center of the triangle is less than $\frac{2}{3}$ of a side's length. However, the center of the triangle divide the (shortest) straight line from each corner to the opposite side 2 to 1 which corresponds to the mean absolute deviation of beliefs of $W^B_{RE}\left(\mathrm{RCM}_{S/T}\right) = \frac{2}{3}$. Therefore, we have to adjust the distance in the figure accordingly.

In figure 4 two examples of misaligned beliefs are shown. The first example denoted by small triangles can be observed if transaction prices are around the dividend of state M_B: H_A and $NOTH_B$ informed participants predict mostly state M_B. The $NOTM_B$ informed who know that this prediction is not correct bet on state H_B which can be ruled out by the $NOTH_B$ informed. The second example denoted by squares shows a situation in which H_A and $NOTM_B$ informed predict state H_B and the $NOTH_B$ informed choose their highest possible state, i.e. state M_B. As a result prices can be expected to be closer to the H_B dividend than to the M_B dividend.[24]

2.5 Information Trap

Misaligned beliefs are not sufficient to cause the evolution of an information trap. Otherwise, the mutually inconsistent beliefs at the beginning of a trading year, which are due to different private information, would never allow information aggregation. However, there are some incentives to trade since expected values differ across information groups and since subjects may have different risk attitudes. In contrast, in a market without differences in participants' expected values and risk adjusted positions, trading and bidding will cease at a point different from the RE equilibrium because no participant has an incentive to trade. In addition, there can exist situation in which all traders with the same information cannot buy or sell certificates because they have either no money to buy or certificates to sell.[25] As a result, these traders' information is lost to the market and therefore other traders cannot learn that their current expectation is not correct.[26]

Definition: An *information trap* occurs if (i) beliefs are misaligned and (ii) traders have no incentive to trade.

[24] In principle, it is possible to establish a connection between a period's average transaction price and market participants' average beliefs by projecting the triangle on the y-axis (parallel to the $H_B L_B$-line). However, we can offer no suitable explanation about the exact relation between prices and beliefs which is beyond the scope of this paper.

[25] In most sessions there existed only a short selling restriction. Allen, Morris and Postlewaite (1993) showed that even a finite number of trading opportunities does not rule out the existence of bubbles if each agent has private information and faces a short sale constraint in the future with positive probability. Thus, we conducted some sessions without any short selling restriction.

[26] The difference between our definition of information traps and the traps Forsythe, Palfrey and Plott (1982) tried to construct in their experiment in session 4 is quite obvious at this point. They constructed a situation in which subjects trading only based on their private information would have lead to no trading in period B and thus the period B information would be lost to the market (p. 547f) resulting in a loss of welfare. In their simple setting, subjects avoided this particularly designed trap. Notice, that *information traps* in our experiment are not artificially induced and require a special type of misaligned beliefs.

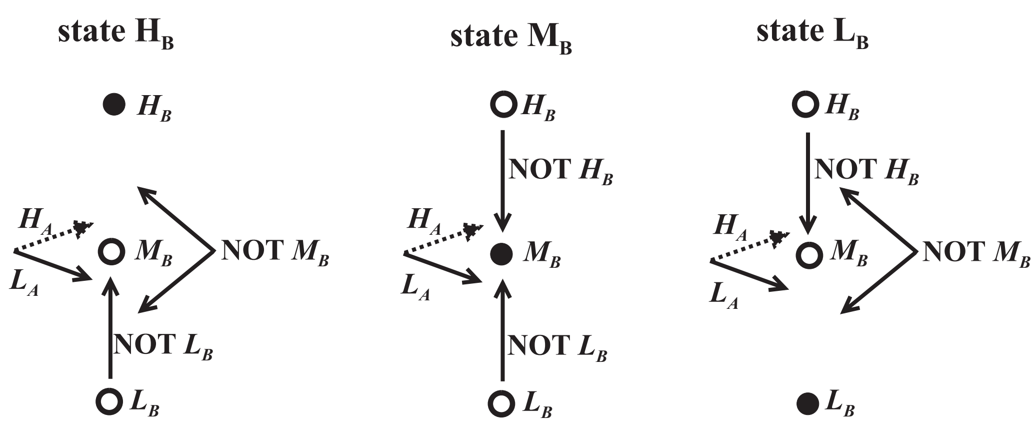
Most riskless trades can be executed by either $NOTH_B$ or by $NOTL_B$ informed subjects since they can reduce the range of possible dividend payments by 200 cu. Period A informed can reduce the range by 100 cu and $NOTM_B$ informed cannot rule out any extreme dividend payment. For example, $NOTH_B$ informed will sell certificates as long as they can receive more money than they would in state H_AM_B and thereby holding the price down at this level as long as they have certificates left to sell. Once they are sold out or they decide to sell no additional certificates because of paralysis they have reached an (effective) boundary, i.e. these participants can do nothing which would cause other traders to change their beliefs, making them aligned. As a result prices can go up to a level on which the remaining participants can agree on since they do not recognize that one information group is forced to stay out of the market. It is crucial at this point that $NOTH_B$ informed subjects have no other way communicating their information than via market transactions.

2.6 Information Aggregation Process

In this section we show which specific aggregation process would lead to RE-prices in this experiment. This exercise is necessary to understand why information might be aggregated in some situations whereas nonaggregation can be observed in others. In section 4 we will identify specific types of behavior and demonstrate their implications on the process of information aggregation. As noted in section 2.5 information $NOTH_B$ or $NOTL_B$ can be used to reduce the range of possible dividend payments by 200 cu and thus drive the price to the M_B range. Period A information only helps to rule out one extreme state (either L_AL_B or H_AH_B) and is therefore less valuable. Figure 5 shows the possible price impact of private information in period A depending on the correct state in period B.

Figure 5: Price impact of private information

The potential price impact based on private information is displayed in this figures depending on the three possible states in period B. For example, information H_A leads to a slightly higher expected value than without any private information in period A. Thus, if these participants use only their private information this will lead to higher prices than without any information.



Information aggregation should be achieved easily if state M_B occurs because both $NOTH_B$- and $NOTL_B$-informed traders will drive prices to the M_B dividend range. Period A informed will then be able to use their information to reach the RE equilibrium. However, if information $NOTM_B$ is available it will be crucial in which ordering price signals will reach the market. $NOTH_B$ or $NOTL_B$ are the most important information in these situations because $NOTM_B$-informed traders need this to decide whether state L_B or state H_B will occur. Note that $NOTM_B$-informed traders should wait until they receive price signals to update their beliefs since certificates' expected value does not change based exclusively on their own private information.

The problem is to distinguish between signals from period A informed and from the other period B information group. Period A informed traders have to deal with the following dilemma: on one hand they can only adjust slightly their expected value and hence their trading position and should wait until period B information is relatively obvious but on the other hand their information is only valuable in period A. As a result both, period A informed traders and $NOTM_B$-informed traders have to find a balance between greed, i.e. speculating early based on fuzzy information, and fear, i.e. betting on the wrong side of the market.

In general, information aggregation can be achieved if period B information is aggregated first and then adjusted by period A information. More specifically, the most extreme information ($NOTH_B, NOTL_B$) has to be incorporated into prices first. Second, the remaining period B information should have its impact on prices before finally period A information enter into the process. Information can be aggregated by sequences of bids (to buy), asks (to sell) or by transactions. The interpretation of price changes and the resulting updating process is the crucial part of the information aggregation process.

3. Results

This section starts with several general results and observations before specific and more detailed results are discussed. Each session lasted between 2.5 and 3 hours. Subjects earned on average 35.59 US$ or 43.33 DM within a range of 5.00 US$ (-23.76 DM) to 78.16 US$ (86.13 DM) by collecting dividends.[27] In addition, participants received between -2.80 US$ (-1.25 DM) and 5.10 US$ (5.00 DM) for their bets on the true state or state combination. Taking all periods of all sessions (=236 periods) together our data base consists of 10851 bids, 10313 asks, 11849 executed transactions and belief data of all traders and all periods.[28]

Figure 6 contains a typical trading picture for three years (year 4-6) within one session (9511271).

For every period the RE-price is displayed as a solid (horizontal) line. Diamonds, squares, and circles denote asks, bids, and transactions, respectively. Obviously, some information is aggregated in both, period A and period B but the aggregation is not always complete.[29] Average beliefs correspond directly

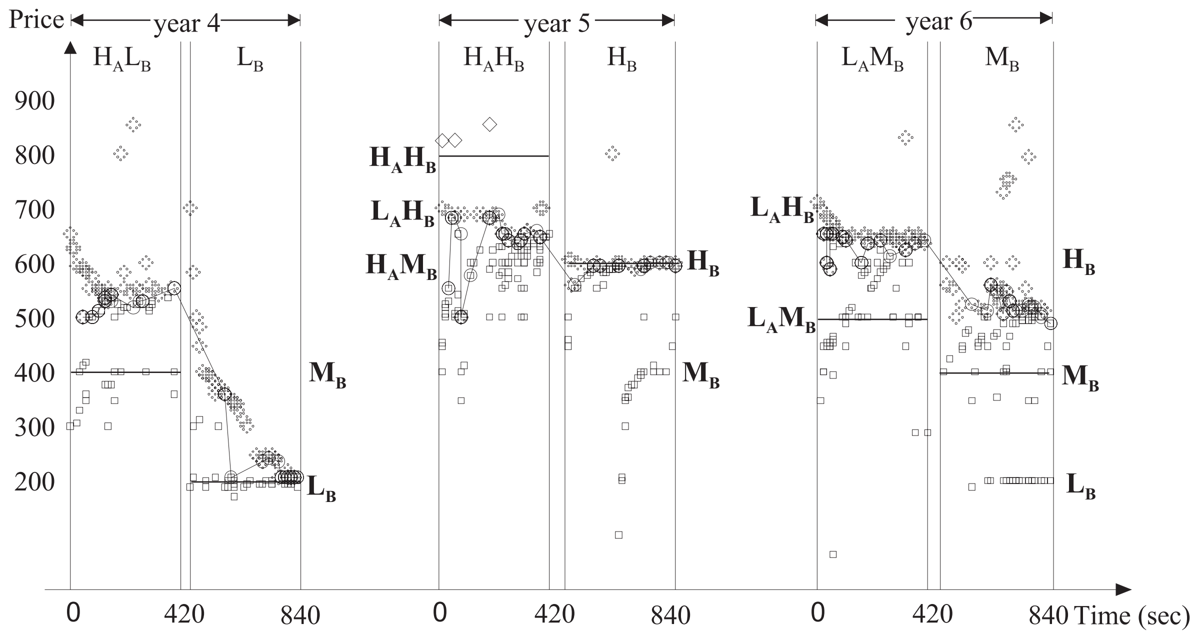
[27]This payment numbers are computed separately for participants at CalTech and Universität Mannheim and reflect differences due to certain restrictions at both universities. In Mannheim, one participant had to pay 23.76 DM at the end of the session. All other participants earned a positive amount of money.

[28]In session 9510281 no belief data was collected and in session 9511041 subjects had no choice between two bets.

[29]This is one of the best aggregation examples especially in year 4.

Figure 6: Bids, asks and transactions: session 9511271, trading years 4, 5 and 6

For every period the RE-price is displayed as a solid (horizontal) line. Diamonds, squares, and circles denote asks, bids, and transactions, respectively. In this session the dividend payment at the end of period A is 200cu if state L_B occurs. The lowest possible liquidation value (state L_B) is 200cu, too. In trading year 4 the state $H_A L_B$ occurs. As a result, the fundamental value in period A is 400cu. In period B it is 200cu. In trading year 5 state $H_A H_B$ implies a fundamental value of 800cu and 600cu, respectively. The fundamental values in year 6 are 500 and 400 since state $L_A M_B$ occurs.



with observed prices in these periods.[30]

Analyzing price data even in this simple environment is complicated because aggregation can occur not only via transactions but also via bids and asks. In addition, even the time between two transactions and/or between bids and asks may convey information. To avoid imposing assumptions about which data to use, we report price data as average transaction prices per period.[31]

3.1 Phenomena of information aggregation at the aggregate level

In this section, results are presented using data aggregated over all subjects depending on the realized state but regardless of their individual private information. The evidence is based on transaction prices and beliefs which are collected at the end of each period. In order to compare the results of as many sessions as possible and since the dividend structure is the same except for a constant we compute the deviation between the RE-prediction and the average transaction price of each period. Based on this

[30] It is not obvious whether individual beliefs are the result of observed prices or vice versa.

[31] The main results do not change if we calculate a last price for each period or if we take the average price of the last (two) minute(s). The reason for this is a rather fast stabilization of transaction prices at some level, i.e. prices suggest a fast convergence to a certain level which all participants can agree on. In addition, using average price data has the big advantage that occasionally observable weird closing prices do not have an impact on the result especially since subject tend to ignore them anyway.

data the mean and standard deviation is defined for each of the possible six (three) states in period A (period B) which is displayed in table 3. The individual predictions are counted twice if a high bet is chosen.[32]

Table 3: Average transaction prices compared to RE and most common beliefs in sessions without H_B-claims

In the upper half of this table for each of the six possible states in period A the (second) most common prediction $Mode_1(Mode_2)$ is presented. $Freq_1(Freq_2)$ is the weighted frequency of the (second) most common prediction. A prediction with an associated high bet was counted twice. *PD* denotes the *P*rice *D*ifference between the average transaction price and the RE price of a period. *Mean (PD)* and *StdDev (PD)* are the mean and standard deviation of these price differences, respectively, which are computed over data from *# Periods*.

Period A	H_AH_B	L_AH_B	H_AM_B	L_AM_B	H_AL_B	L_AL_B
Mode_1	$\mathbf{H_AM_B}$	L_AH_B	H_AM_B	L_AM_B	$\mathbf{H_AM_B}$	L_AL_B
Freq_1	0.388	0.287	0.586	0.476	0.336	0.333
Mode_2	H_AH_B	L_AM_B	H_AH_B	H_AM_B	H_AL_B	L_AM_B
Freq_2	0.223	0.279	0.167	0.267	0.280	0.304
Mean (PD)	-206.44	-131.04	-20.96	-1.58	114.29	207.24
StdDev (PD)	59.49	53.60	42.31	97.41	86.01	21.61
# Periods	9	20	11	16	18	4
Period B	H_B	H_B	M_B	M_B	L_B	L_B
Mode_1	H_B	H_B	M_B	M_B	L_B	L_B
Freq_1	0.478	0.444	0.767	0.808	0.466	0.800
Mode_2	M_B	M_B	L_B	H_B	M_B	M_B
Freq_2	0.375	0.406	0.122	0.126	0.351	0.133
Mean (PD)	-86.54	-120.76	31.55	47.70	194.79	155.74
StdDev (PD)	54.16	48.46	43.49	66.92	104.98	122.87
# Periods	9	20	11	16	18	4

The difference between the six possible states in period A is quite striking. As table 3 shows the most common predictions are wrong in two states, H_AH_B and H_AL_B. The most common prediction is H_AM_B in these two cases. Moreover, the relative frequencies of the (correct) most common predictions vary between 28.7% (state L_AH_B) and 58.6% (state H_AM_B). Remember, that according to the RCM model the correct prediction should be the most common with a $\text{Mode}_1 = \frac{5}{18}$ (=27.8%) in period A and $\text{Mode}_1 = \frac{4}{9}$ (=44.4%) in period B assuming all subjects taking the same bet. It is obvious that a lot of traders are not able to predict the correct state and thus they do not reach the RE equilibrium in period A.

Table 3 shows, too, for states H_AM_B and L_AM_B that average transaction prices are close to, i.e. less

[32]The results would not change dramatically if each prediction is counted once regardless of the associated bet.

than 48 cu away from the RE level. In addition, the most common beliefs with their associated relative frequencies indicate that information aggregation is observable especially at the end of period B. For example, in state $H_A M_B$ average transaction prices are on average only -20.96 cu (31.55 cu) below (above) the RE level in period A (B). The most common prediction over 11 periods is the correct state $H_A M_B$ (58.6% of all weighted predictions) at the end of period A. 16.7% of weighted predictions indicate state $H_A H_B$ (second most common prediction) as being correct which might explain prices above the RE-level.

But table 3 also demonstrates that severe information aggregation problems exist in some other states. If state $H_A L_B$ occurs the mean of price differences compared to RE in period B is 194.79 cu which is equivalent to the M_B level. In addition, only 46.6% of all weighted predictions are correct compared to 44.4% predict by RCM, i.e. assuming no learning in addition to private information. Moreover, the most common prediction ($H_A M_B$) is wrong in period A and state M_B still receives 35.1% of weighted predictions in period B compared to 27.8% predicted by RCM.

The results for state $L_A H_B$ are remarkable, too.[33] In both periods a tie between the most common and the second most common prediction is observable. Notice, that the frequency of the correct most common prediction in both periods is equal to the RCM prediction. The second most common predictions is higher than predicted by RCM (27.9% vs. 19.4% (period A); 40.6% vs. 27.8% in period B). These predictions indicate that subjects have learned that state $H_A L_B$ or $L_A L_B$ will not occur. We will see later using mean absolute deviations of beliefs whether traders can distinguish between the remaining states or not. Another the RE-level. In period B the mean difference of -120.76cu is close to the PI equilibrium, i.e. the highest expected value for any information group based only on private information ($NOTL_B$): In 10 out of 20 B-periods the average transaction price is less than 30 cu away from the PI-level whereas in period A 15 out of 20 average transaction prices are below the PI-level (see figure 7 below). Since the PI-level is 100 cu below the RE-level in both periods this observation is evidence for some learning from period A to period B although information aggregation is not perfect.

In state $L_A L_B$ predictions and mean price differences in period B can be used as evidence of information aggregation and against it, respectively, because 80% of the weighted predictions are for the correct state L_B but the average price difference (+155.74cu) strongly favors state M_B. State $H_A H_B$ is predicted less often than the RCM model suggests and the most common prediction is false (state $H_A M_B$, 38.8%). In addition, the price difference to RE (-206.44cu) strongly supports the most common prediction. The improvement in both, predictions and price deviations indicate learning although this is not sufficient to arrive at the RE-level. These mixed results for states $H_A H_B$ and $L_A L_B$ are the reason why we do not focus on them in particular analyzing data at the aggregate level. However, these states will be included in the analysis at the information group level.

Result 1: Information aggregation can be observed but the reliability depends on the state.

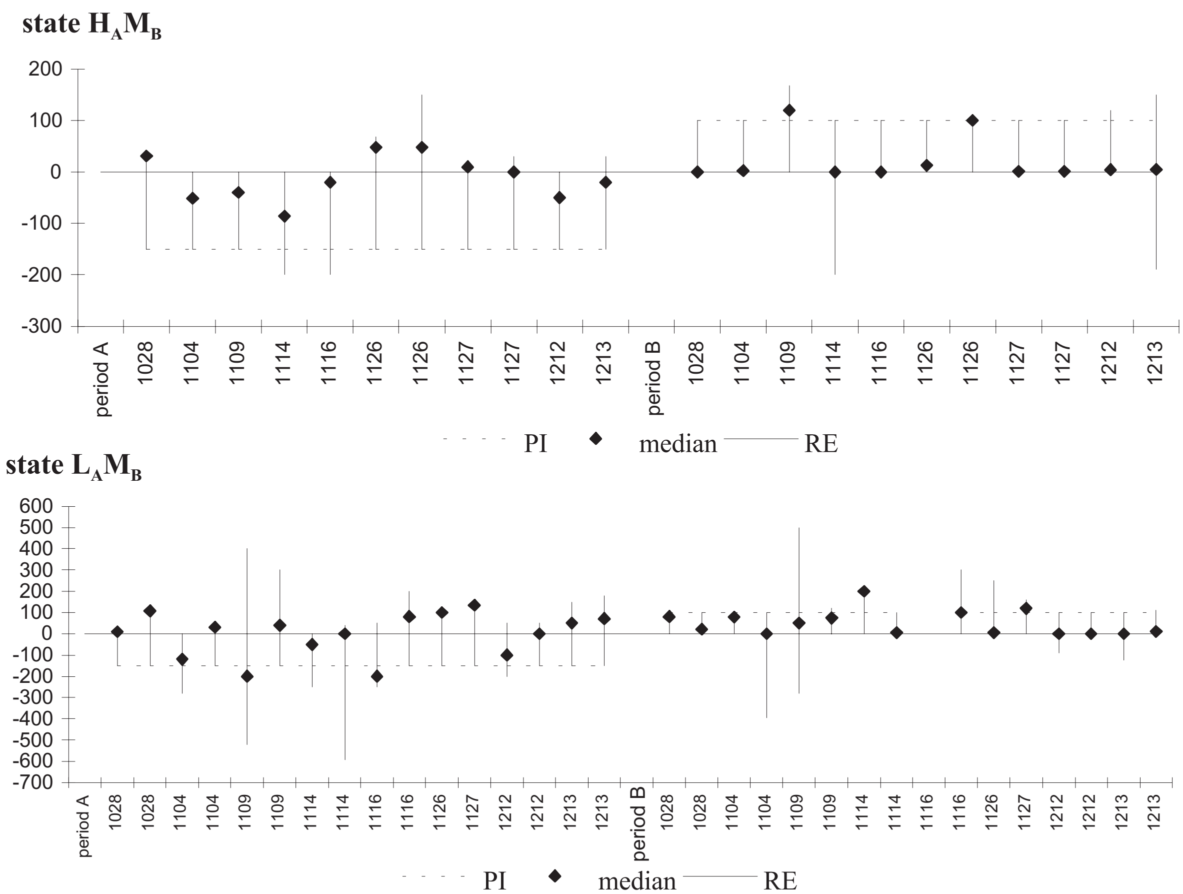
Result 1.1: States with reliable information aggregation are $H_A M_B$ and $L_A M_B$.

[33] Note that states $L_A H_B$ and $H_A L_B$ are equivalent concerning the information structure.

Based on average transaction prices aggregation occurred in 9 of 11 A- and B-periods in state $H_A M_B$ as can be seen in figure 7a. The deviation from the RE-level is not significantly (t=-0.928 (A); t=1.693 (B)) different from 0 in both periods. If state $L_A M_B$ occured aggregation was achieved in 6 out of 14 periods in both periods, i.e. aggregation did not improve in period B. On the contrary, average deviation from the RE-level increased and is significantly positive in period B (t=3.292).

Figure 7: Deviation of transaction prices from the RE-level: states $*_A M_B$, no H_B-claims

The median, maximum and minimum deviations of transaction prices from the RE-level are shown for each session in which either state $H_A M_B$ or state $L_A M_B$ occurred. In addition the deviation of the private information equilibrium is displayed.



In figure 7 the median transaction price deviations from the RE-level are shown for both, period A and period B. All transaction prices are weighted with the traded quantity. In addition, the PI-level deviation and both the maximum and minimum deviations are provided. The number of the session is displayed, too. The same session number indicates that there were more than one observation per session.

As discussed before information aggregation need not necessarily to be achieved via transactions. It can also be the result of bids to buy or asks to sell. Moreover, traders might abstain from trading for whatever reasons although their beliefs are correct. Therefore, the distribution of beliefs is important to determine whether or not market participants have aggregated all available information. The data in table 4 contains all predictions weighted by their associated bets, i.e. high bets are counted twice.[34]

Table 4: Distribution of beliefs in sessions without H_B-claims

In this table the distribution of beliefs for all sessions without H_B-claims are shown for both, period A and B. Correct predictions are in **bold**. To determine whether period A information is aggregated at the end of this period the sums $H_A{*}_B$ and $L_A{*}_B$ with ${*}_B \in \{H_B, M_B, L_B\}$ are provided. In addition, the p-value of the binomial test (bitest) is given.

Period A

	Prediction								
State	H_AH_B	L_AH_B	H_AM_B	L_AM_B	H_AL_B	L_AL_B	$H_A{*}_B$	$L_A{*}_B$	bitest=$\frac{5}{18}$
H_AH_B	**27**	22	47	8	9	8	83	38	0.8716
L_AH_B	33	**76**	45	74	22	15	100	165	0.2622
H_AM_B	27	2	**95**	19	16	3	138	24	0.0000
L_AM_B	8	20	60	**107**	15	15	83	142	0.0000
H_AL_B	30	28	84	29	**70**	9	184	66	0.4430
L_AL_B	1	6	2	21	16	**23**	9	60	0.1327

Period B

	Prediction			
State	H_B	M_B	L_B	bitest=$\frac{4}{9}$
$(H_A)\,H_B$	**65**	51	20	0.3684
$(L_A)\,H_B$	**140**	128	47	0.3579
$(H_A)\,M_B$	21	**145**	23	0.0000
$(L_A)\,M_B$	30	**193**	16	0.0000
$(H_A)\,L_B$	57	110	**146**	0.3699
$(L_A)\,L_B$	6	12	**72**	0.0000

In table 4 a summary of all predictions aggregated over all sessions depending on the occurring state is presented for both periods. This table provides a first impression about the belief data for computing the mean absolute deviation of beliefs from RE, i.e $W^{A,B}_{\mathrm{RE}}(\mathrm{RE}) = 0$ (see figure 8). Period A information is aggregated only if more than two thirds of the traders predict the period A state correctly since one third of all traders has perfect information about this state. Without any information aggregation at least $\frac{5}{18}$ ($\frac{4}{9}$) of all predictions should be correct under the RCM assumptions at the end of period A (B).[35] The binomial tests support result 1 that in period A and B states ${*}_A M_B$ with ${*}_A \in \{H_A, L_A\}$ can be predicted better than random guessing.

[34] Again, the results are essentially identical without incorporating the bets.

[35] The reference value for each state in period A would be $\frac{5}{18}$ if all subjects guessed because one third of the participants can rule out three of the six possible states with their information about period A. The other two thirds of the subjects can rule out just two states, thus $\frac{1}{3} * \frac{1}{3} + \frac{2}{3} * \frac{1}{4} = \frac{5}{18}$. In period B, one third of the traders is uninformed and tow thirds know that one of two possible states will occur: $\frac{1}{3} * \frac{1}{3} + \frac{2}{3} * \frac{1}{2} = \frac{4}{9}$.

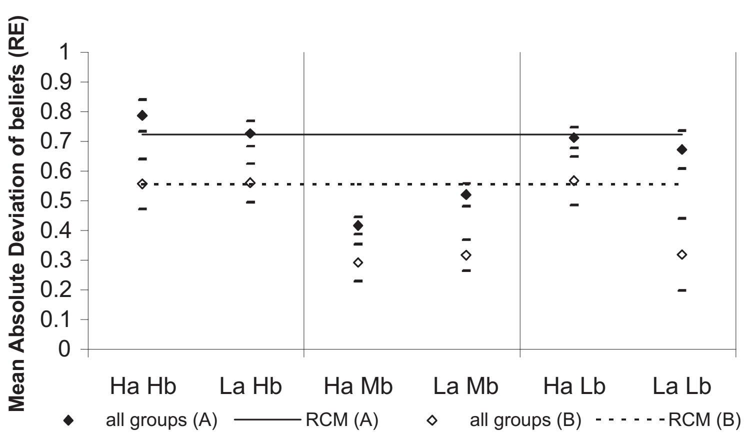
The aggregated beliefs in state H_AM_B confirm result 1.1 since all available information is aggregated in period A although the aggregation is not perfect. In period A 95 of 162 predictions are correct which is significantly larger than the prediction by RCM. The ratio of correct predictions of the period A dividend is 138 to 24. In period B information is aggregated, too, since 145 out of 199 predictions are correct which is again significantly larger than the proportion predicted by RCM. In state L_AM_B the B-information is aggregated both, in period A and period B which is indicated by the result of the bitest. In period A (B) 107 out of 225 (193 out of 239) predictions are correct. However, A-information is not aggregated in period A since traders could not distinguish between H_A and L_A which predicted at a ratio of 60 to 107.[36]

In contrast to the evidence offered by the transaction prices most traders predict the A-information correctly (60 out of 69). The B-information is only partially aggregated in period A because traders are only convinced that $*_AH_B$ and H_AM_B can be ruled out. In period B 72 out of 90 predictions are correct. If state H_AH_B, H_AL_B or L_AH_B occurred aggregation would not be observed in period B. This evidence will lead to result 2 and will be analyzed later.

Computing the mean absolute deviation of beliefs for each period and averaging by states offers a different perspective about the belief data by emphasizing extreme cases of either aggregation or misaligned beliefs. Figure 8 shows the average mean absolute deviations of beliefs depending on the realized state computed against the RE-benchmark.

Figure 8: Average mean absolute deviations of beliefs with standard errors depending on the realized state: all information groups combined

This figure shows the average mean absolute deviations of beliefs depending on the realized state computed against the RE-benchmark. The mean absolute deviation of beliefs of the RCM model from RE based on all period A predictions is denoted by $W^{\mathrm{A}}_{\mathrm{RE}}(\mathrm{RCM_{all}}) = \frac{1}{2} * \left(\frac{7}{36} + \frac{7}{36} + \left(1 - \frac{10}{36}\right) + \frac{3}{36} + \frac{3}{36} + \frac{6}{36}\right) = \frac{13}{18}$. In period B the mean absolute deviation of beliefs is $W^{\mathrm{B}}_{\mathrm{RE}}\left(\mathrm{RCM_{all}}\right) = \frac{1}{2} * \left(\frac{5}{18} + \frac{5}{18} + \left(1 - \frac{8}{18}\right)\right) = \frac{5}{9}$. In addition to the average mean absolute deviation of beliefs the one standard error interval is provided.



[36]Remember that A-informed traders should always predict the correct A-dividend and thus the expected ratio of random guessing should be 1:2.

For each of the six states the average mean absolute deviation of beliefs from RE (=0) is marked by a diamond. The diamond is filled in period A and unfilled in period B. In addition, the one standard error interval is provided. The straight line (broken line) at $\frac{13}{18}$ $\left(\frac{5}{9}\right)$ in period A (B) is the second benchmark: the mean absolute deviation of beliefs of the RCM model.

Obviously, information aggregation can be observed on average for states H_AM_B and L_AM_B in both, period A and period B but the aggregation is not complete. The average mean absolute deviation of beliefs for state H_AM_B is 0.417 at the end of period A. The RCM model predicts an average mean absolute deviation of beliefs of $\frac{13}{18}$ (=0.722) which is significantly higher than the observed distance. At the end of period B the average mean absolute deviation of beliefs has been reduced to 0.292 compared to $\frac{5}{9}$ (=0.556) for the RCM model moving further towards RE. The average mean absolute deviations of beliefs in state L_AM_B in period A and B are 0.521 and 0.317, respectively.

In state L_AL_B the aggregation takes place in period B $\left(W_{\text{RE}}^{\text{B}}\left(L_AL_B, \text{all}\right) = 0.319\right)$ although in period A almost no deviation from the RCM line can be seen $\left(W_{\text{RE}}^{\text{A}}\left(L_AL_B, \text{all}\right) = 0.672\right)$. Moreover, the mean transaction price difference from RE has not indicated such an improvement in information aggregation either which demonstrates the necessity and value to analyze both prices and beliefs.[37] However, aggregation does not occur in all states as the results for states H_AH_B, H_AL_B and L_AH_B will show.

Result 1.2: States with unreliable information aggregation are H_AL_B and L_AH_B.

Again, the evidence is based on our two data sets, i.e. prices and beliefs. In figure 9 the median deviation of transaction prices from the RE-level are provided for each period depending on the states $*_AH_B$ and $*_AL_B$ (see figure 7 for states $*_AM_B$).[38]

Nonaggregation is obvious looking at figure 9. In state H_AH_B average transaction prices are even lower than the PI-level (=-150cu) in 7 out of 9 cases in period A. But in period B prices suggest partial information aggregation since they are closer to state H_B than to state M_B in 8 out of 9 periods. However, in six periods prices are still closer to the PI-level (=-100cu) than to the RE-level. In 17 of 20 A-periods with state L_AH_B prices are closer to PI (=-150cu) than to RE. In nine B-periods prices are closer to M_B than to H_B with an additional four periods in which prices are exactly halfway (=-100cu) between both states. If state L_B occurs in period B and state H_A (L_A) is observed in period A, 13 of 18 (three of four) average transaction prices are closer to the PI-level which is equivalent to state M_B! The same result holds in period A for these two states.

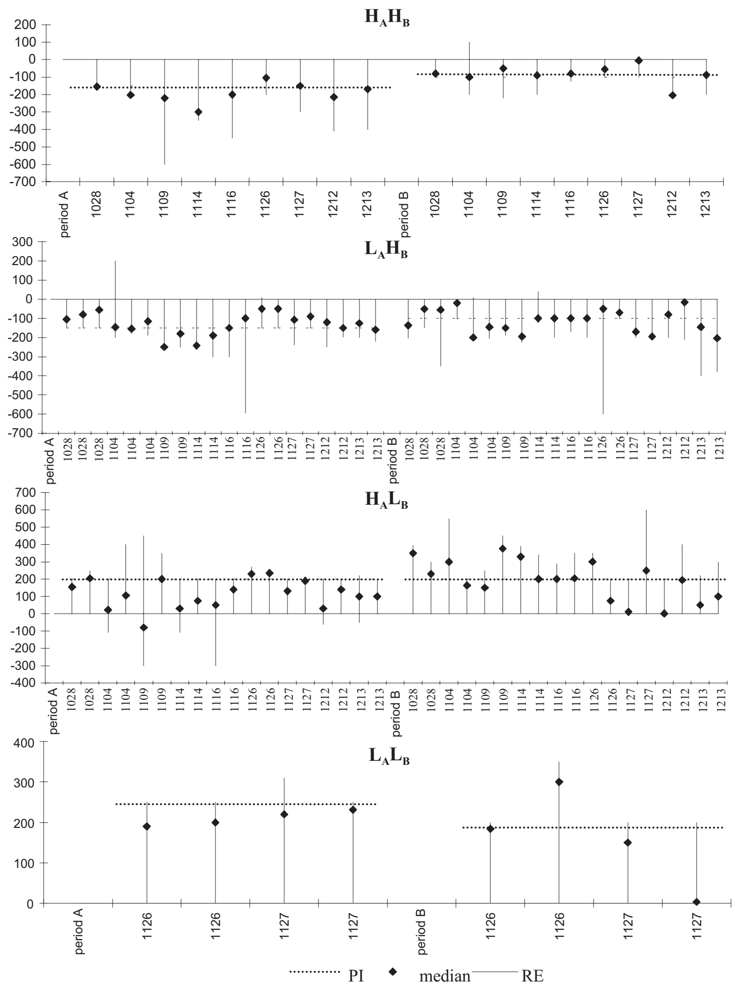
Based on the average mean absolute deviations of beliefs aggregated over all information groups depending on the state which are displayed in figure 8 it is obvious that no aggregation occurred in states H_AH_B, L_AH_B and H_AL_B in both periods A and B. The average mean absolute deviation of beliefs is almost exactly at the RCM level which means that random predictions would yield the same result. Notice that the average mean absolute deviation of beliefs is closer to the maximum distance (=1) than

[37] The aggregation via bids to buy and asks to sell is one possible explanation. However, it is not obvious why this occurs in this state. But it should be remembered that we have only four periods with state L_AL_B in sessions without an H_B-claim market.

[38] The elimination of 5% or 10% most extreme price deviations within each period does not change the result.

Figure 9: Deviation of transaction prices from the RE-level: states $*_A H_B$ and $*_A L_B$, no H_B-claims

The median, maximum and minimum deviations of transaction prices from the RE-level are shown for each session in which either states $*_A H_B$ or states $*_A L_B$ occurred. In addition the deviation of the private information equilibrium is displayed.



to RE (=0) in both periods. However, table 4 shows, too, that the distribution of predictions differs from the RCM prediction. For example, there are too many prediction of state $H_A M_B$ in states $H_A H_B$ and $H_A L_B$ compared to the RCM model. This is another hint that even nonaggregation might have some regularities.

An obvious, but wrong inference would be to conclude that evidence of table 4 suggests a M_B bias, namely that subjects tend to predict state M_B too often regardless of the realized state which might explain why we observe information aggregation in states $H_A M_B$ and $L_A M_B$. We will show in the next subsection with data for each information group that the information is aggregated in both states and that the nature of misaligned beliefs leads to this puzzling result at the aggregated level.

3.2 Phenomena at the information group level

As mentioned briefly in the previous section the aggregation of belief data across all information groups covers crucial evidence to explain the observed nonaggregation. Since all market participants receive common dividends and have full knowledge about the information structure, information should have been aggregated. Thus, it is surprising that nonaggregation seems to happen frequently and to be state dependent. Belief data aggregated by information groups will help to explain result 1.

The reliability of information aggregation is not only state dependent but depends also on the private information as can be seen in figure 10. For each of the six states the average mean absolute deviation of beliefs (filled symbol) with one standard error intervals (unfilled symbols) is displayed. Results for information groups H_A and L_A are marked with circles. Diamonds, squares and triangles are used for information groups $NOTH_B$, $NOTM_B$ and $NOTL_B$, respectively.

The mean absolute deviation of beliefs of the RCM predictions (solid line) for A-informed traders is $W_{RE}^{A,B}(RCM_{\text{A-info}}) = \frac{2}{3} = \frac{1}{2} * \left(\frac{1}{3} * \frac{1}{3} + \frac{1}{3} * \frac{1}{3} + \frac{1}{3} * \frac{2}{3}\right)$ in both, period A and period B since these traders have to choose between three states. B-informed traders can eliminate only two states in period A which leads to a RCM value of $W_{RE}^{A}(RCM_{\text{B-info}}) = \frac{3}{4} = \frac{1}{2} * \left(\frac{1}{4} + \frac{1}{4} + \frac{1}{4} + \frac{3}{4}\right)$ (broken line). In period B the RCM value for these information groups is $W_{RE}^{B}(RCM_{\text{B-info}}) = \frac{1}{2} = \frac{1}{2} * \left(\frac{1}{2} + \frac{1}{2}\right)$ because traders can predict one of two (ex ante) equally likely states. Results for period A are shown in figure 10a and for period B in figure 10b.

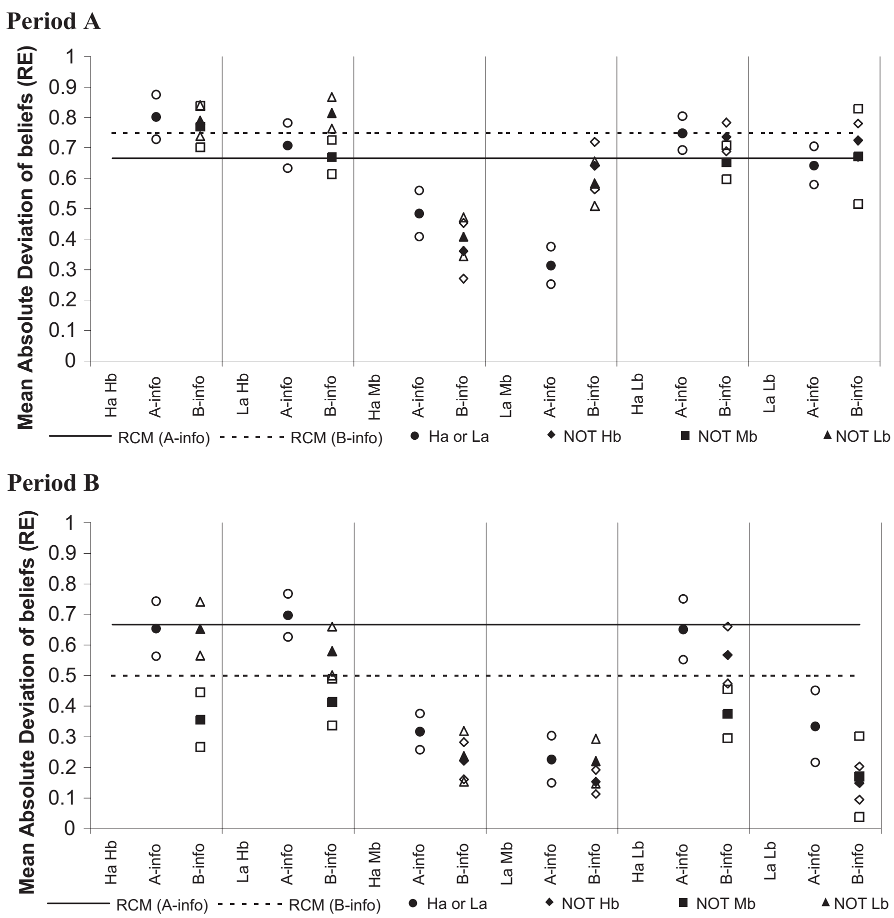
For example, in state H_AH_B in period A the average mean absolute deviation of beliefs for information group H_A (=A-info) is 0.8 (filled circle) with a standard error of 0.073. The RCM prediction for this group is $\frac{2}{3}$. The average mean absolute deviations of beliefs of information groups $NOTM_B$ (squares) and $NOTL_B$ (triangle) are 0.77 and 0.79, respectively, which is slightly higher than the RCM value of 0.75.

The information group data confirms our results 1.1 and 1.2, i.e. reliable information aggregation can be observed in states H_AM_B, L_AM_B and L_AL_B, but almost no aggregation can be found in the other states. States H_AM_B and L_AM_B are aggregated on average by *all* three information groups both in period A and B indicated by the average mean absolute deviations of beliefs which are significantly smaller than the RCM distances. However, aggregation is not complete since on average about 1.5 out of 5 traders are predicting the wrong state in period B. Sometimes, aggregation is perfect. For example, in period 16 of session 9511271 with experienced subjects the mean absolute deviations of beliefs for each information group are equal to zero, i.e. every trader predicts the correct state $(H_A)\,M_B$. In the previous period A aggregation can be observed within the B-informed groups but the H_A-informed traders have not learned (as a group) anything since the mean absolute deviation of beliefs is $\frac{2}{3}$. Periods with (almost) perfect aggregation can be found for each of the six states.

Figure 10 reveals differences between information groups, too. Most striking is the learning by $NOTM_B$-informed traders in every state. Information $NOTH_B$ obviously hinder in learning the correct state $(H_A)\,L_B$ and thus the mean absolute deviation of beliefs in period B is not only greater than that of $NOTM_B$-informed subjects but also greater than predicted by RCM: $NOTH_B$-informed traders "learn" the wrong state, i.e. M_B. The same is true for $NOTL_B$-informed market participants if state H_B occurs. Moreover, A-informed subjects do not learn either in states with $NOTM_B$ information. Thus, possession of $NOTM_B$ information leads to partial aggregation but this information does not reach the market. If

Figure 10: Average mean absolute deviations of beliefs with one standard error intervals depending on the realized state for all information groups

In this figure the mean absolute deviations of beliefs are shown separately for all information groups depending on the realized state. The mean absolute deviation of beliefs of the RCM model from RE based on period A predictions of a specific *info*rmation group is denoted by $W_{RE}\left(RCM_{\text{info}}\right)$. Thus, the RCM baseline for period A informed participants is $W_{RE}^{A,B}\left(RCM_{\text{A-info}}\right) = \frac{2}{3} = \frac{1}{2} * \left(\frac{1}{3} * \frac{1}{3} + \frac{1}{3} * \frac{1}{3} + \frac{1}{3} * \frac{2}{3}\right)$. The baseline for period B informed subjects is $W_{RE}^{A}\left(RCM_{\text{B-info}}\right) = \frac{3}{4} = \frac{1}{2} * \left(\frac{1}{4} + \frac{1}{4} + \frac{1}{4} + \frac{3}{4}\right)$ in period A and $W_{RE}^{B}\left(RCM_{\text{B info}}\right) = \frac{1}{2} = \frac{1}{2} * \left(\frac{1}{2} + \frac{1}{2}\right)$ in period B. Results for information groups H_A and L_A are marked with circles. Diamonds, squares and triangles are used for information groups $NOTH_B$, $NOTM_B$ and $NOTL_B$, respectively. The one standard error interval is denoted by the information group's unfilled symbol.



learning occurs it can be mostly observed in period A since period B improvements seem only to be the result of private information. This indicates the existence of a relatively stable situation in period B.

Most of our following analysis will focus on period B because differences in beliefs have a more obvious impact on prices since dividends differ at least by 200 cu. In addition, the information situation is simpler. A-informed traders are uninformed in period B and thus cannot help with the aggregation process. As before, we analyze the relative frequencies of individual beliefs including the strength of beliefs for each of the possible three states. Then we compute the mean absolute deviation of beliefs for each information group. Mean absolute deviations of beliefs which are greater than the RCM prediction for B-informed traders are a signal for the existence of misaligned beliefs. Based on this data we can support the next result:

Result 2: Misaligned beliefs exist.

One of the most extreme examples can be observed in trading year 7 of session 9511091 (state $L_A H_B$). The mean absolute deviations of beliefs in period A for information groups $NOTM_B$, $NOTL_B$ and L_A are 0.5, 1 and 0.75, respectively. These numbers do not necessarily indicate misaligned beliefs. However, all three groups have a mean absolute deviation of beliefs of 1 in period B, i.e. all $NOTM_B$-informed predict state L_B and all $NOTL_B$-informed predict state M_B. In addition, none of the L_A-informed traders believes that state H_B will occur. However, information groups' average beliefs are spread out over the whole range of possible outcomes as figure 11 shows for all possible states in period B.

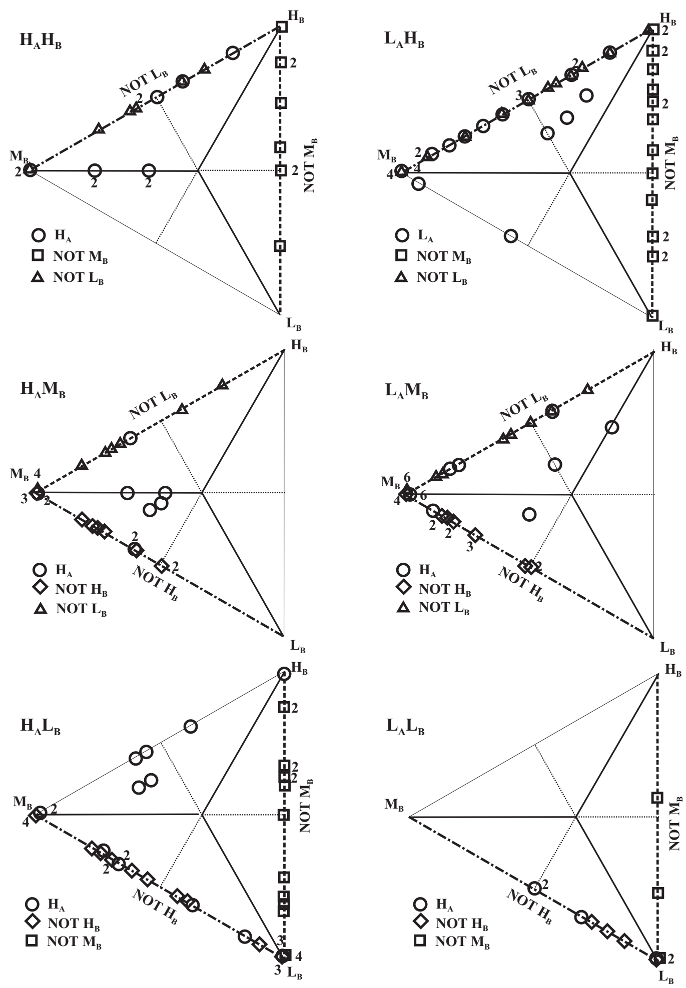
The distribution of mean absolute deviations of beliefs in states $H_A M_B$, $L_A M_B$ and $L_A L_B$ clearly underline result 1 that information aggregation is reliable. Mean absolute deviations of beliefs which are greater than the RCM prediction can be observed only in a few periods. As further data will show, there exist no period in which more than one information group has an average belief which suggests nonaggregation. In states $H_A H_B$ and $L_A H_B$ partial aggregation is achieved since there are only some periods in which $NOTM_B$ informed traders predict state L_B. Period A informed who are uninformed in period B basically rule out state L_B in all but one period. However, the distribution of information groups' mean absolute deviations of beliefs clearly demonstrates that aggregation is not reliably achieved. Finally, in state $H_A L_B$ nonaggregation seems to be most common since the mean absolute deviation of beliefs of the H_A-informed traders is close to the maximum distance in eight out of sixteen periods. In addition, in seven periods at least two information groups have mean absolute deviations of beliefs which are close to the maximum distances as table 5 shows. But, aggregation is observable in some periods and clustering around 0.5 indicates random guessing in other periods.

Extreme cases in which an information group is completely misaligned are rather rare. Only in one period all three groups have perfect misaligned beliefs. In three periods two groups' beliefs correspond to the maximum mean absolute deviation of beliefs. The next step is to relax the definition of misaligned beliefs to understand the often huge deviations between transaction prices and the certificates value. A-informed traders are uninformed in period B and thus can serve as an indicator of the degree of information aggregation. If their beliefs lead to a mean absolute deviation of beliefs between the RCM value $\left(\frac{2}{3}\right)$ and the maximum distance (=1) this information group will be labeled as misligned in this period. B-period informed subjects whose RCM value is $\frac{1}{2}$ have information and thus will be only seen as misaligned if the mean absolute deviation of beliefs is not less than 0.75 which is half way between the RCM value and the maximum distance. Table 5 offers evidence how reliable information aggregation is aggregated and how often misaligned beliefs evolved.

In table 5 a period is counted under "aggregation" ($0 \leq W_R E \leq 0.25 \forall$info groups) if at least one group has a mean absolute deviation of beliefs of less than $\frac{1}{4}$ which is half way between the RCM distance

Figure 11: Mean absolute deviations of beliefs for all B-periods depending on the realized state for all information groups

In this figure the mean absolute deviations of beliefs based on beliefs at the end of period B are shown for all information groups depending on the realized states in both periods. Results for information groups H_A and L_A are marked with circles. Diamonds, squares and triangles are used for information groups $NOT H_B$, $NOT M_B$ and $NOT L_B$, respectively.



(=0.5) and the RE distance (=0) for period B informed.[39] Confirming previous evidence the data in table 5 demonstrates that aggregation is reliable in states H_AM_B, L_AM_B and L_AL_B. It is not reliable in the other three states in which misaligned beliefs occur frequently. In addition, it can be seen that misaligned beliefs in state H_AL_B are affecting at least two groups more often than in state L_AH_B. In general, situations with neither aggregation or nonaggregation are not often observed. Moreover, there exists no period in which an information group identifies the correct state and another group is misaligned. At this point we can address the M_B-bias, i.e. overprediction of state M_B would yield the same result.

[39] Alternatively, one can compute the sum of all three mean absolute deviations of beliefs to identify misaligned beliefs and aggregation. The results are very similar but do not offer as much structural insights since $\frac{7}{5} = 1 + \frac{1}{5} + \frac{1}{5} = \frac{2}{5} + \frac{3}{5} + \frac{2}{5}$.

Table 5: Misaligned beliefs and aggregation in sessions without H_B-claims

In this table information groups' beliefs in each B-period is classified. If the mean absolute deviation of beliefs of one group is smaller than 0.25 the period will be classified as aggregated. A mean absolute deviation of beliefs of more than 0.75 leads to the classification of misaligned. All other cases remain undecided.

period B	$(H_A)\,H_B$	$(L_A)\,H_B$	$(H_A)\,M_B$	$(L_A)\,M_B$	$(H_A)\,L_B$	$(L_A)\,L_B$
aggregation	2	5	7	12	5	4
undecided	2	2	2	0	2	0
one group misaligned	1	4	1	1	2	0
2 or 3 groups misaligned	3	6	0	0	7	0
$\sum$	8	17	10	13	16	4

This is not the case mainly for two reasons. First, traders had no incentive to predict always state M_B since it occurred only with probability $\frac{1}{3}$ and wrong predictions lead to a smaller payment. Second and more important is the following observation:

Observation: Misaligned beliefs of $NOTH_B$- and $NOTL_B$-informed traders can only occur if they predict state M_B too often.

Result 2 motivates an important question. Can misaligned beliefs persist or are they only a transitory state in the process of information aggregation? This question is closely connected to the question whether information traps exist which are a self confirming equilibrium in the sense of Fudenberg and Levine (1993a,b).

Result 3: Information traps exist.

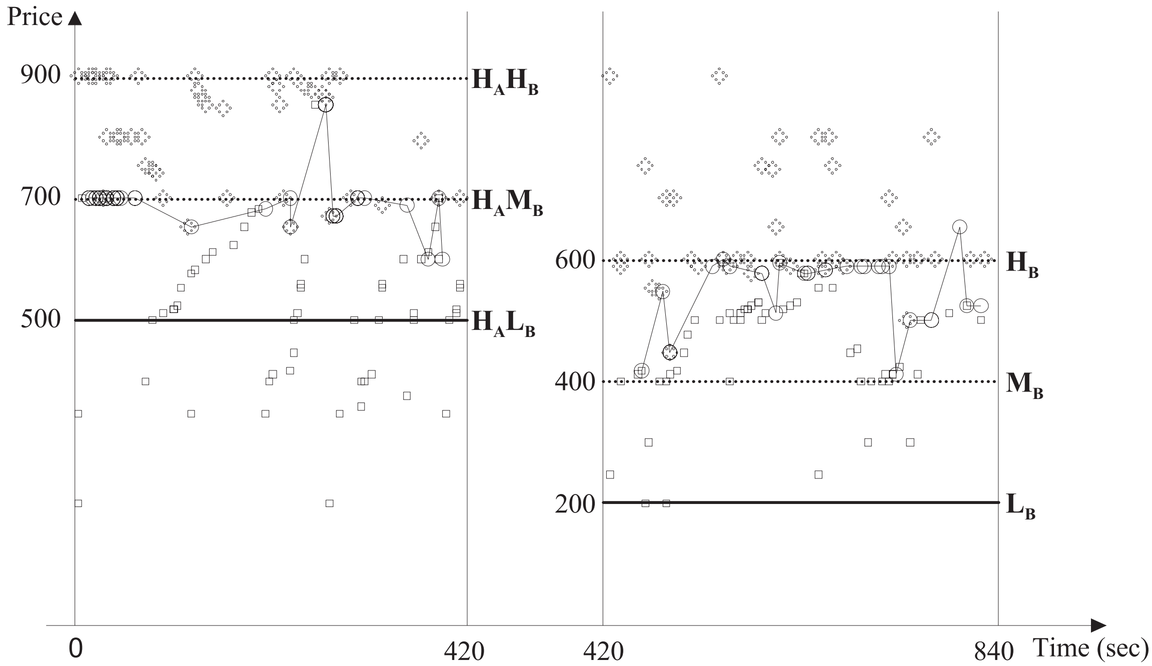
As the following example shows information traps occur. As in this example, we will concentrate on traps in state H_AL_B in which the short selling constraint binds. Then, we will explain why information traps can be observed in other states, too.

In this trading year of session 9511091 state H_AL_B occurred. In period A most transactions are made at a price of about 700cu which are supported by relatively small bid/ask-spreads. This pattern clearly indicates state H_AM_B. At the end of period A state H_A is announced and trading opens in period B exactly 300cu lower at 400cu. After about two minutes transaction prices reach 600cu indicating state H_B and stay there until the end of the trading year. At this point all H_A-informed and four of the five $NOTM_B$-informed traders predict state H_B. All but one of the $NOTH_B$ traders who know that this cannot be correct predict state M_B. All except three traders have ruled out the correct state L_B at the end of period A, too. To establish the existence of an information trap, it is necessary to show that those participants with the crucial information, i.e. the information which is needed to switch to the RE equilibrium have no incentive or no opportunity to do so. As a result these participants can neither transmit their information to the market nor profit from the "obvious" mispricing. In this particular state (H_AL_B) and prices indicating state H_B, the most crucial information is $NOTH_B$.

The question to be addressed is why this information seems to be lost to the market. Since we assume

Figure 12: Information Trap: session 9511091, trading year 4

In this trading year state $H_A L_B$ occurs which corresponds to a fundamental value in period A of 500cu and in period B of 200cu. Between both periods participants receive the dividend of 300cu. Diamonds, squares, and circles denote asks, bids, and transactions, respectively. The solid horizontal line indicates the RE-level. Other possible levels are drawn as broken horizontal lines.



that all traders prefer earning more money $NOTH_B$-informed traders should sell as many certificates as possible regardless of their risk attitude if the price is higher than the highest possible dividend payment based on their information, i.e. 400cu in period B. The numbers of certificates a trader can sell is limited to her initial endowment. Therefore, the definition of when a subject reaches a boundary seems to be obvious in our design: due to the shortselling restriction in most sessions but no credit restriction, subjects are at the boundary only if they have sold all their certificates. But the information of a subject will be lost for the market in any case if a subject does (can) not use her information, i.e. submit offers to buy or to sell certificates or does not trade based on her private information.[40] Therefore, the definition of an effective boundary is necessary. A subject's effective boundary is reached after her last trade within a trading year. Note that the notion of an effective boundary captures all cases in which a trader has no incentive to trade.

Conjecture: $NOTH_B$-informed subjects reach an effective boundary in period A.

To prove this conjecture is difficult for two reasons. The first problem is that you do not have an incentive to trade in an equilibrium regardless of whether this is the RE-equilibrium or a trap. Moreover, you will not trade if you fear that you do not understand why the observable price is contradicted by

[40]Some behavioral explanations such as paralysis, scalping and plunging will be discussed in the next section.

your own private information, i.e. you are paralyzed (see section 4.1). The second problem is to define the situation when a subject has reached her effective boundary. To illustrate the problem suppose you have information $NOTH_B$ and thus you are selling certificates whenever the price is higher than H_AM_B in period A. But when you observe enormous buying pressure you decide to wait in order to let prices increase even further to earn more money collecting the period A dividend and selling the other certificates in period B. Thus your information is lost to the market although you sell certificates in period B.

Nevertheless, we can provide evidence that the short selling restriction stabilized potential information traps in state H_AL_B. A potential information trap exists if the average price deviation from RE in period B is greater than 100 cu, i.e. prices indicate a different state. In these periods 28 out of 65 traders (=43%) did not change their position in period B whereas only 11% of uninformed traders (H_A) and 27% of $NOTM_B$-informed did not change their position in period B. In contrast, about two thirds of the traders (regardless of their private information) changed their position in period B in periods with information aggregation and state H_AL_B.

In the other state (L_AH_B) in which information traps frequently occurred an effective boundary could not be found. However, average net changes of positions show why aggregation is prevented. $NOTM_B$-informed traders buy on average 0.52 certificates in period A and <u>sell</u> 2.52 certificates in period B if an information trap occurs in state L_AH_B. In contrast, they sell 2.16 certificates in period A and buy 0.08 certificates in B if aggregation can be observed. Aggregation seem to depend on the trading behavior of $NOTL_B$-informed participants. If they buy 7.46 certificates in period B aggregation will be achieved. However, if they buy the same number of certificates in the whole trading year but only 4.25 in period A, an information trap will occur. The reason for the necessity to buy certificates very aggressively is the behavior of L_B-informed traders who sell about five certificates in period A. If these traders' selling pressure becomes too strong so that $NOTM_B$-informed traders begin to exclude state H_B, the information $NOTL_B$ is lost for the market.

In state H_AL_B the situation is just the other way around. If $NOTH_B$-informed (-4.18) can counter the buying pressure of H_A-informed (+3.19) no information trap will be formed. However, if the buying pressure is too high (+4.89) in period A and $NOTH_B$-informed do not sell enough (-4.62) a trap will develop which cannot be reversed in period B even though $NOTH_B$-informed sell additional certificates (-1.10). Similarly, in state H_AH_B aggregation depends most heavily on the trading behavior of $NOTL_B$-informed participants. If they buy enough certificates in period A (+4.09) then all information will be aggregated. If they do not buy enough in period A (+1.82) aggregation will not be achieved until the end of the trading year even though they buy on average 5.25 additional certificates in period B.

Summing up, information traps occur if the most valuable information within a trading year, i.e. $NOTH_B$ or $NOTL_B$ are not clearly signaled to the market in period A. Even if in period B additional trades might offer the information, too, the signal jam in period A carries over and thus the most valuable information is lost. In addition, it is obvious why states $*_AM_B$ are aggregated more reliable: in these situations both information, $NOTH_B$ and $NOTL_B$, exist in the market. To which extent individual behavior, such as "scalping" and "plunging" contribute to the development of misaligned beliefs and information traps will be studied in section 4.1.

3.3 Robustness of information traps?

Information traps are not observed in this experiment for the first time. Sunder (1992) reports three trading periods within his experiment in which a non revealing equilibrium occurred which was caused by the short selling restriction (=effective boundary):

> "Convergence to wrong prices occurred in later periods of these markets when many traders seem to have become accustomed to being able to infer state from price. (...) all informed traders were on the selling side and they became inactive after selling their endowment of two certificates because of the restriction on short sale. Other traders had no way of knowing that the informed traders had become inactive. Knowing that at least some trader(s) in the market had perfect (and therefore superior to their own) information, the [un]informed seemed willing to rely on the market to learn the state from prices. The blind leading the blind, they arrived at the wrong conclusion in these three cases" (Sunder 1992, p. 690).

Note that contrary to Forsythe and Lundholm (1990) non revelation seemed to be the result of (perceived) experience. On the other hand, Camerer and Weigelt (1991) did not observe information mirages in later periods, i.e. traders seemed to be able to distinguish between uninformed and informed trades. Thus, we have to check whether experience might reduce the number of information traps. Sunder mentioned four conditions under which aggregation was not achieved in his experiment in some periods. These conditions hold in our experiment, too, although they are not all necessary for the existence of information traps. First, informed traders should have "perfect information while the uninformed had none" (Sunder 1992, p. 691). In our experiment, the information was perfect since all private information was always correct but not complete for each individual trader. Thus, the information structure seems to influence the aggregation process, too. Second, there were enough informed traders to achieve information aggregation at least in some states. Third, information traps can arise even without a binding short sale restriction. Finally, traders' inactivity cannot be observed by others in association with their private information since no communication besides bidding and trading was allowed.

Obviously, the next step is testing the robustness of information traps. We study the effect of an additional state contingent claim market, of the removal of the short sale restriction and of traders' experience.

The introduction of an additional H_B-contingent claim market should remove all information traps.[41] Through the additional market the information $NOTH_B$ can be transmitted directly into the market and thus eliminate all traps in states $*_A L_B$. Moreover, inactivity in this market should signal state H_B. As a result, signals from the additional market can easily be learned by other participants leading to (better) information aggregation. It does not seem to be necessary to introduce a full set of state contingent claim markets as in Plott and Sunder (1988).

Result 4: The addition of an H_B-contingent claim market improves information aggregation but it does not eliminate all information traps.

[41] Alternatively, an additional L_B-contingent claim market would have the same effect.

Table 6 in comparison to table 3 offers first hints that the H_B-claim market improves information aggregation. However, in some states information aggregation is (still) a problem or even worse than without the H_B-claims.

Table 6: Average transaction prices compared to RE and average frequencies of beliefs in sessions *with H_B-claims*

In the upper half of this table for each of the six possible states in period A the (second) most common prediction $Mode_1(Mode_2)$ is presented. $Freq_1(Freq_2)$ is the weighted frequency of the (second) most common prediction. A prediction with an associated high bet was counted twice. *PD* denotes the *P*rice Difference between the average transaction price and the RE price of a period. *Mean (PD)* and *StdDev (PD)* are the mean and standard deviation of these price differences, respectively, which are computed over data from *# Periods*.

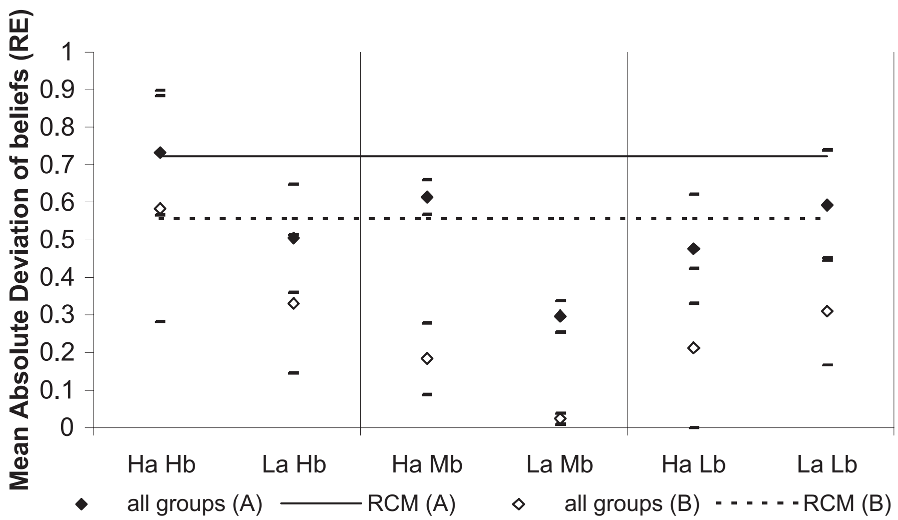
Period A	H_AH_B	L_AH_B	H_AM_B	L_AM_B	H_AL_B	L_AL_B
Mode_1	$\mathbf{H_AL_B}$	L_AH_B	H_AM_B	L_AM_B	H_AL_B	L_AL_B
Freq_1	0.286	0.556	0.388	0.714	0.582	0.456
Mode_2	H_AH_B	L_AM_B	L_AM_B	H_AM_B	L_AM_B	H_AL_B
Freq_2	0.224	0.153	0.388	0.179	0.164	0.237
Mean (PD)	-270.66	-181.18	-115.77	10.41	82.82	52.53
StdDev (PD)	109.74	63.79	21.66	20.77	70.06	54.26
# Periods	6	8	6	6	6	12
Period B	H_B	H_B	M_B	M_B	L_B	L_B
Mode_1	$\mathbf{M_B}$	H_B	M_B	M_B	L_B	L_B
Freq_1	0.469	0.697	0.806	0.970	0.883	0.786
Mode_2	H_B	M_B	H_B	H_B/L_B	M_B	M_B
Freq_2	0.391	0.253	0.145	0.015	0.083	0.176
Mean (PD)	-127.07	-69.05	55.68	2.21	74.70	86.93
StdDev (PD)	104.91	54.22	89.21	5.31	91.32	70.96
# Periods	6	8	6	6	6	12

Comparing the data of table 6 with table 3 shows that aggregation improves with H_B-claims especially in states H_AL_B and L_AL_B. For example, the average price deviation from RE drops from -195cu to 75cu and the prediction frequency for the correct state increases from 0.466 to 0.883 in state H_AL_B. In general, aggregation is achieved more reliably in all states but state H_AH_B. In this state either aggregation is achieved or an information trap occurs at state M_B. Basically the same inference can be drawn from the average mean absolute deviations of beliefs which are shown in figure 13.

The comparison of figures 8 and 13 shows an that mean absolute deviations of beliefs are on average smaller. With the exception of state H_AH_B, a clear movement from the RCM benchmark to the RE level can be observed in period A. In period B the mean absolute deviation of beliefs is decreasing further

Figure 13: Average mean absolute deviations of beliefs with standard errors depending on the realized state: all information groups combined (with H_B-claims)

This figure shows the average mean absolute deviations of beliefs depending on the realized state computed against the RE-benchmark in sessions with an additional H_B-claim market. The mean absolute deviation of beliefs of the RCM model from RE based on all period A predictions is denoted by $W_{\text{RE}}^{\text{A}}(\text{RCM}_{\text{all}}) = \frac{1}{2} * \left(\frac{7}{36} + \frac{7}{36} + \left(1 - \frac{10}{36}\right) + \frac{3}{36} + \frac{3}{36} + \frac{6}{36}\right) = \frac{13}{18}$. In period B the Würtz distance is $W_{\text{RE}}^{\text{B}}(\text{RCM}_{\text{all}}) = \frac{1}{2} * \left(\frac{5}{18} + \frac{5}{18} + \left(1 - \frac{8}{18}\right)\right) = \frac{5}{9}$. In addition to the average mean absolute deviation of beliefs the one standard error interval is provided.



and is in state $L_A M_B$ on average almost equal to zero, i.e. reaching the RE level.[42] However, the mean absolute deviation of beliefs in state $H_A H_B$ is equal to the RCM benchmark. But the huge standard deviation in period B supports in combination with the most common and the second most common prediction (see table 3) the notion that unreliable information aggregation exists with extreme values, i.e. misaligned beliefs and perfect aggregation in different trading years.

The development of one of these traps based on perfect misaligned beliefs is described in section 4.2. The basic problem is the fast reaction of the H_B-claim market to the information $NOTH_B$ if this information exists. Since this fast movement in two thirds of all trading years results in no trading opportunity for the worthless certificates some traders try to unwind their position regardless of their own information. Using then the price movement in the H_B-claim market to infer (wrongly) that state H_B will not occur leads to an information trap since no market participant has the information that H_B is the correct state. Summing up, the introduction of an H_B-claim market improves the reliability of information aggregation but information traps still occur.

Result 5: Removing the short selling restriction does not improve information aggregation.

Eliminating the short selling restriction is certainly another intuitive way of eliminating most information traps in state $H_A L_B$ because they can exist under this condition only if all subjects with the crucial infor-

[42]The mean absolute deviations of beliefs do not differ between information groups in sessions with H_B-claims.

mation stop trading for endogenous reasons, i.e. they are not willing to participate in risky transactions. Note however that information traps in state $L_A H_B$ occur even with unlimited money supply! Therefore, another explanation seems to be appropriate to understand the stability of misaligned beliefs and information traps. As the following example ($H_A L_B$) shows the removal of the short selling restriction decreases the average price deviation from the RE level but misaligned beliefs and an information trap still occur. In this example with short selling, a situation arises in which two thirds of the participants prevent inadvertently the other third from offering their information. In session 9512121, year 4, prices stay at the M_B-level in period B because as soon as prices go up someone with information $NOTH_B$ will sell one unit. On the other hand a price drop is prevented by the period A informed who exclude state L_B from the possible states because of what they have "learned" in period A. As a result, the $NOTM_B$-informed who know that the observed transaction prices are wrong are not able to communicate their information to the market especially since the observed price is equal to their expected value assuming risk neutrality. Thus they have no incentive to trade.[43] In this situation, the other two information groups have aligned beliefs predicting the wrong state and have no incentive to take additional risk. As a result, misaligned beliefs and the information trap are stable.[44]

As mentioned, using experienced participants might be another way to eliminate information traps. The experiment of Forsythe and Lundholm (1990) demonstrate that information aggregation improves significantly with subjects' experience and if they are completely informed about the dividend and information structures. The information structure was public knowledge in all sessions in our experiment. Moreover, all subjects received the same state dependent dividend per certificate in all sessions since Plott and Sunder (1988) have shown that aggregation results are (c.p.) best with common dividends.

Result 6: Experience helps but information aggregation problems remain.

In sessions 9511261 and 9511271 we checked the effect of experience by inviting subjects who participated in earlier sessions.[45] In general, experienced subjects were better able to aggregate information and to avoid getting into an information trap. However, traps still occurred which is the reason why we included the data in the general analysis. At this point, the question remains how much experience subjects need to aggregate information always. It is not obvious, that more experience increases the chances of information becoming completely aggregated as a special session shows that is not included in the above analysis. However, as the results with the H_B-claim market show, more experience might lead to more extreme forms of MAB.

The process of writing this paper and the discussions with colleagues and Ph.D. students lead to this

[43] Even if they try the other information groups have enough resources to keep prices from moving away from the M_B level. These other groups are convinced that this is the correct state and therefore the traders take every "certain profit" they can get.

[44] Since the removal of the short selling restriction does improve information aggregation at most only slightly we included these sessions in our general analysis.

[45] The subjects did not know that they would participate in the same experiment until they arrived in the lab. As a result, they were not able to coordinate their strategies. In addition, we had a mixture of previous subject groups in each of the two sessions to avoid a group effect.

special session in which short selling was allowed and all twelve participants had to attend a presentation about the nature of an information trap. In addition, one of the co-authors participated in this session. The good news is that information aggregation could be observed at the end of each trading year even without an additional H_B-claim market. However, to achieve this aggregation the trading volume (between just six traders) reached a maximum of 150% of initially distributed certificates and mispricing at the end of period A was higher than 200 cu. In addition, all subjects had the strong desire, besides earning money, not to get into an information trap which might have prevented them, too.

An interesting result from related research is worth mentioning at this point, too. Plott, Wit and Yang (1997) conducted parimutuel betting markets in which traders placed bets on which of six states would occur. Bets on the state which actually occurred were paid off from the losing bets placed on states that did not occur. Some of their sessions used a six-state structure like ours: a third of the traders could eliminate three of the states and a third each could eliminate two states, so collectively they knew exactly what the state was. Contrary to our results, the parimutuel betting markets aggregated information well, i.e. most of the total money was bet on the correct state when the betting markets closed. Their results show that trading institutions other than double auctions may aggregate information differently (and eliminate information traps). The optimal strategy in these betting markets is to wait until the very last second before placing a bet. As a result, no one can learn anything from (not existing) transactions and has to place his bets according to his private information which leads in these markets to information aggregation.[46]

4. Behavioral concepts and theoretical speculation

In this section we discuss some possible explanations illustrated by examples how information traps can be caused. The data generated by this experiment do not allow a detailed statistical analysis because the few restrictions imposed on the subjects' trading behavior allows too much variation in individual behavior and the resulting price process. In addition, beliefs were collected only at the end of each period and thus cannot serve as an explanation for the dynamic of an information trap. Nevertheless, it is useful to study typical behavior and generate some post hoc theory.

4.1 Behavioral concepts

It appears that three types of non-classical decision rules which we call "paralysis", "scalping", and "plunging", may contribute to the formation of information traps. In almost every observable trap some traders are "paralyzed", i.e. not making riskless profits by buying or selling which contributes to traps by keeping information from reaching the market. "Scalping" is observed when a single trader buys <u>and</u> sells heavily in a period, and ends with no substantial net change in holdings. A scalper, by design, does not

[46] Their results also suggest that as traders gain experience, information traps could become more likely, not less likely, in parimutuel markets. The reason for this conjecture is that in some sessions with experienced traders, these traders tried to manipulate the markets by betting on a state they knew was impossible, in order to lure other bettors to bet on that state and eventually collect their money by later betting on the correct state. See Camerer (1987) for a related phenomenon, in which more experienced traders produce larger probability biases in asset markets.

try to move the price but simply tries to benefit from small price movements which are mean-reverting. As a result, scalping contributes to traps in two ways: It keeps the market from getting out of a trap, and it adds noise or "signal-jamming" which makes it difficult for traders to infer information from prices.

Looking at several examples with an information trap one might have the suspicion that "plungers" are causing the trap. "Plunging" occurs if a trader who knows that some subset of states are possible decides early in a period that one of the states is "very likely", and trades aggressively on her belief.[47] Plunging is a special form of overconfidence. For example, $NOTM_B$-traders know the state is either H_B or L_B and sometimes bet heavily on a hunch that the state was "certainly" L_B. Plunging may contribute to a trap because plungers will buy heavily from traders who have information indicating the plunger's hunch is wrong, often buying all the available shares. The actions of plungers can also convince other uninformed traders with the same information to make the same bet unless better informed traders counter this aggressive trading.

Consider the following example: Subject 1 in session 9512121, year 4 ($H_A L_B$) who had the information H_A is clearly a plunger since she/he bought 27 certificates within period A (without having any information about the second period) at an average price of about 50 cu less than the expected value based on the private information. Her/his buying of 27 certificates accounted for 84% of all transactions in this period. Although all participants could see (using an additional screen) that only one trader was buying all these certificates the buying pressure convinced them that state L_B would not occur and thus an information trap started.

Note however, that there is no obvious evidence that plungers are causing information traps since they exist in aggregation and nonaggregation. A test of net changes in positions depending on whether information was aggregated in period B (less than 100 cu deviation from RE) or not, showed no significant differences in the extent of plunging. One explanation for this result is the fact that plungers who bet on the correct state will force the market to aggregate all available information because no participant has contradicting information to the observed price movements. Thus, although plungers might contribute to the evolution of an information trap their existence is not a sufficient condition.

Scalpers identified by their high trading volume do not contribute significantly to the development of traps, too, since their existence is observable both in trading years with and without scalpers. As mentioned above, scalpers introduce additional noise in the price discovery process and thus might support the influence of plungers.

Introducing more participants in this experiment to reduce the effect of an individual player might have some appeal because this can reduce the influence one participant might have in this type of experiment. However, every additional subject increases the probability of observing individual mistakes

[47]Some of these behaviors might be explained by decision rules that are nonexpected utility maximizing. For example, timidity and plunging are the opposite extremes of subjective expected utility maximization with non-additive beliefs, which allow extreme aversion or preference for betting in uncertain situations (e.g., Gilboa and Schmeidler (1989) and Ghirardato (1997)). These decision rules capture phenomena like pessimism and optimism. That is, a timid or paralyzed trader is one who pessimistically fears that whatever action she takes will turn out wrong. A plunger is the opposite, believing that whatever hunch she has will turn out right.

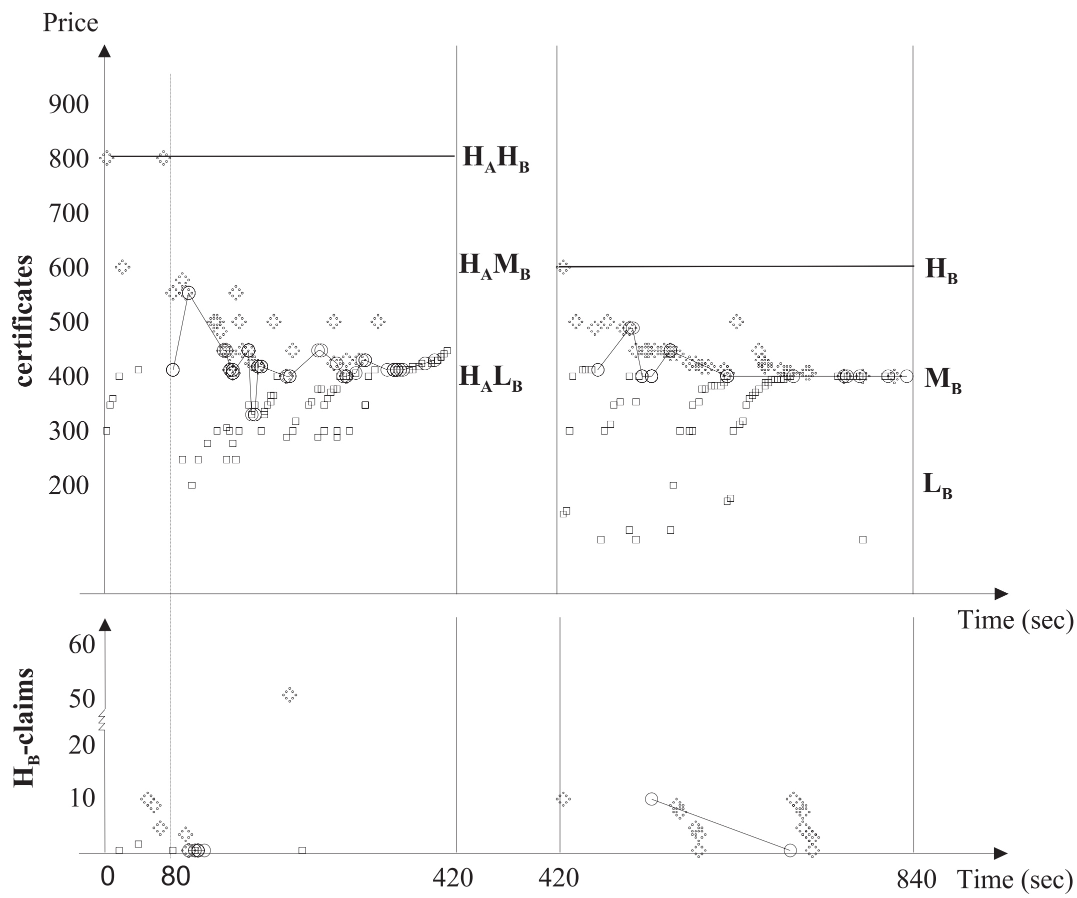
during the aggregation process which can lead to the formation of misaligned beliefs and information traps. Moreover, more subjects can create more noise in the market and thus prevent the aggregation. It is not clear, whether the reduced relative influence will dominate the increased probability of individual mistakes.

4.2 Speed and timing

The question how the information aggregation process really works is influenced not only by subjects' decisions but also by the timing of these decisions. If for example offers to sell (buy) certificates are quickly accepted it is reasonable to conclude that the participant who bought (sold) the certificates has information indicating that the offered price is too low (high). In addition, fierce competition may force the price of offers to sell quickly down indicating information $NOTH_B$ in this experiment. Trading year 5 of session 9511281 is an impressive example for the effect of speed and it's misinterpretation. The offers and transaction prices of the certificate market (upper half) and the H_B-claim market (lower half) are shown in figure 14.

Figure 14: H_B-claims cause nonaggregation

The RE-price is displayed as a solid (horizontal) line for both periods. Diamonds, squares, and circles denote asks, bids, and transactions, respectively. The trading data of the certificate market are displayed in the upper half. The H_B-claim data is shown in the lower half.



This example shows an information trap which is caused by the H_B-claim market. In general, the existence of an H_B-claim market gives $NOTH_B$-informed traders the opportunity to profit directly from their private information, which can be seen in all situations with $NOTH_B$-informed traders. In this example, the distributed information consists of H_A, $NOTM_B$ and $NOTL_B$ implying state H_AH_B (here: =800 cu=200 (H_A) + 600 (H_B)).

The early offers to sell H_B-claims (see figure 14) push the price close to 0 cu in the H_B-claim market, leading all participants to infer that state H_B will not occur. Note that no subject knows with certainty that the H_B-dividend will be paid, so there is little upward pressure on H_B-claim prices. As a consequence, $NOTM_B$- ($NOTL_B$) informed traders conclude that either state L_AL_B (L_AM_B) or state H_AL_B (H_AM_B) will occur. The H_A-informed subjects are choosing between H_AM_B and H_AL_B.

After 80 seconds the first transaction occurs in the certificate market at a price of about 400 cu which is equivalent to state H_AL_B. Most of the transactions in period A are executed at prices close to 400 cu. At the end of the period a high trading intensity $\left(\frac{\#\text{ offers}}{\#\text{ trades}}\right)$ a increasing prices indicate the development of period B.[48] All $NOTM_B$-informed and three H_A-informed predict state H_AL_B at the end of period B. Five traders predict an M_B-dividend for the end of period B while only one participant believes that H_B will occur in period B.

At the beginning of period B two aggressive $NOTL_B$-informed traders push the price to the M_B-level at 400 cu where prices remain until the end of the trading year. All $NOTL_B$- and all H_A-informed participants predict state M_B at the end of period B which can be translated to Würtz distances from RE of 1. In addition, all $NOTM_B$-informed traders who can rule out this prediction are convinced that state L_B occurs.

In this case the information trap is stable because all participants obviously have no incentive to force the market towards state H_B which is "ruled out" by the H_B-claim market. As expected, $NOTL_B$-informed traders buy a lot of certificates while $NOTM_B$-informed traders who know that state M_B will not occur, sell all their certificates because they believe that the L_B-dividend will be paid. One trader with the $NOTM_B$-information is paralyzed. The trap is stable, too, because even in period A seven traders take the high bet. This number increases to eleven in period B which indicates the high confidence in their guesses.

As in this specific example, timing decisions concerning transactions might offer some insights in general about how misaligned beliefs and traps can occur. Camerer and Weigelt (1991) showed that increased trading intensity indicated noninsider periods which has to be learned by the participants. Sustained "mirages can be thought of as errors in Bayesian inference of information from prices. In early periods, traders have not yet learned the typical price paths in insider and noninsider periods. Noise trading then generates a price path that resembles the path in a previous insider period, to which other traders overreact" (p.490).

As the analysis of information traps (result 3) has already shown, the difference between nonaggregation and aggregation is not the result of differences in overall trading volume or net change of position.

[48] One of the $NOTL_B$ bought 48 certificates (participating in 60% of all transactions) in period A without having a significant price impact.

However, some aspects of trading intensity, i.e. the relation between offers and transactions might offer some insight at which point during a trading year misaligned beliefs might arise. We will focus on the two cases in which information traps developed most frequently: states $H_A L_B$ and $L_A H_B$. As before, trading years are classified as nonaggregation years if the average price deviation from RE is greater than 100 cu in period B. In contrast to Camerer and Weigelt (1991), trading intensity is not significantly different in the first quarter (=105 seconds) of period A.

If state $L_A H_B$ occurs trading intensity in period A is significantly (p=0.081) lower in nonaggregation situations than in aggregation years. More specifically, if there are fewer bids and asks per transaction than the likelihood of an information trap increases. This means that offers are accepted faster in period A especially in the second and fourth quarter. In period B, however, the reverse is true: if information is aggregated the trading intensity will be significantly (p=0.012) higher in nonaggregation trading years especially in the second half of the period. In other words, if information is aggregated less trading per offer occurs. In state $H_A L_B$, the results are similar but not as crisp as in state $L_A H_B$. Trading intensity is only slightly lower in trading years with aggregation than in nonaggregation years (p=0.368) although the difference is significant in the second half of period A (p=0.068). In period B, the trading intensity is significantly (p=0.079) higher in years with information aggregation. This result is based mostly on the trading pattern in the first half of period B. In summary, there are differences in trading intensities between years with information traps and those with information aggregation. These differences are the result of a combination of factors such as plunging and scalping as well as other unidentified reasons.

At this point one might think about how and especially when a subject should act in this experiment to avoid losing money because of trading based on misaligned beliefs. It is obvious that $NOTH_B$ ($NOTL_B$)-informed participants can use their information directly without relying on other than their private information as long as the price is above state $H_A M_B$ (below state $L_A M_B$). Under these circumstances these subjects can trade risklessly. The period A informed can rule out only one extreme dividend payment and therefore are unlikely to get the opportunity of trading without facing the risk of loosing money. Trades by $NOTM_B$-informed subjects are always risky. As a result participants with the information $R \in \{H_A, L_A, NOTM_B\}$ should wait before trading to receive a signal from those participants who can make riskless trades. Otherwise, they will ignore the adverse selection problem that better informed participants accept these offers only if this transaction yield a profit at the expense of the offering participant.

Since the information structure in this experiment is common knowledge it is certain that either $NOTH_B$ or $NOTL_B$ informed participants (if not both) are in the market all participants with another information should do nothing at the beginning of a year. If we assume that all traders do not want to participate in risky trades, $NOTH_B$ and $NOTL_B$ informed should only post offers which would result in a riskless profit if they were accepted. As a result, the offers to sell would go down to the $H_A M_B$-level and the offers to buy would go up to the $L_A M_B$-level, respectively. At this point, the other market participants can update their beliefs using their own information and the signaled information. Then, they might have the opportunity to offer trades which would result in riskless profits until all information is aggregated. Notice, that in this scenario no transaction would ever take place and all available information would be aggregated.

However, as soon as one subject is assumed to be willing to participate in risky trades the feedback of price signals for the updating of beliefs is more complicated because now the updating procedure needs additional assumptions about the risk aversion or willingness to participate in risky trades of all subjects. For example, homogeneity of risk aversion among all participants makes it always possible to interpret the price signals and thus allows information aggregation (without any trades).

4.3 Learning

The question how and when participants in this experiment learn within a trading year or across years within one session can not be answered with our data. To get an answer to this question it is either necessary to collect belief data throughout a trading year or to ask outside observers of the trading process about their beliefs concerning the realized state or the amount of available information at any given time. The question when subjects learn specific pieces of information is especially important since we found a discrepancy in net changes of positions between non aggregation and aggregation: if the period B information is not learned by the end of period A it will not become revealed at the end of period B. In addition, unlearning of information occurs only in period A and not in period B. Thus, collecting real time belief data would help to understand the evolution of information traps and the related information mirages documented by Camerer and Weigelt (1991).

Summing up, the number of information traps can be reduced in several ways such as experience, allowing short sales or introducing an H_B-claim market or even using a completely different market structure such as a call market with indicative prices. However, overconfidence, i.e. plunging or scalping, and paralysis can have a significant effect on information aggregation especially if market participants have no experience how to detect this behavior in the market. Last but not least, you should keep in mind that in this simple setting the general information structure was common knowledge which helps to analyze price movements and thus aggregate all available information.

5. Conclusions

With this experiment the existence of information traps as a result of misaligned beliefs is established in markets with common knowledge about both, the information and the dividend structure. Information traps result from individual non-rational behavior of at least one trader which can lead to misaligned beliefs. Even if some traders realize that beliefs are misaligned they have either no incentive or no market power to do anything against it. In general, prices reveal average beliefs but do not indicate the existence of information traps. Even without short-selling restrictions or with an additional H_B-claim market misaligned beliefs and non revealing equilibria can be observed. H_B-claims and experience reduce but do not eliminate misaligned beliefs and information traps.

Whether our results depend heavily on the symmetry of our period B dividend structure has to be analyzed in the future although every change in the information structure can lead to new problems: For example, if two dividends are close to each other it will be difficult for traders and for the subsequent analysis of the data to differentiate between these two states. In addition, convergence to a wrong price is reported by others, e.g. Sunder (1992), too. The aggregation over two periods is not a general problem as our two sessions with only two states in period B and as Forsythe, Palfrey and Plott (1982) showed.

Misaligned beliefs are often caused by paralysis, plunging or scalping of some traders. A more complete theory of traps might weave these decision rules and other features like supply constraints and the role of H_B-claim prices into a formal, dynamic story about how traps come about and are sustained. Such a story would presumably tell us what treatment variables make traps more or less likely. There are some models with a more detailed structure concerning the distribution of signals, timing of trading and pricing rules to explain a specific kind of asset price movements. For example, a combination of Romer's (1993) two models might offer such a formal, dynamic story and an explanation of rational asset-price movements without news. However, these two models are still based on the assumption that all traders behave always rationally. Gul and Lundholm (1995) provide another interesting model which might explain indirectly what causes the evolution of misaligned beliefs and the resulting information trap. Suppose that an overconfident trader uses his private information too early (relative to rational behavior) or not as suggested by theory. The result is that all other traders update their beliefs correctly but based on the wrong information set which leads to misaligned beliefs as in our third example. All three models together with our experimental results provide some useful insights for further theoretical and experimental research.

Appendix

A. Instructions

General

This is an experiment in the economics of market decision making. Various research foundations have provided funds for this research. The instructions are simple, and if you follow them carefully and make good decisions, you might earn a considerable amount of money which will be paid to you in cash.

In this experiment we are going to conduct a market in which you will be a participant in a sequence of market years. Each year consists of two periods, the first of which will be called "Period A", and the second "Period B". Each period lasts 7 minutes which will be announced at the beginning of each period. The markets for certificates that have a one year (=two period) life. The certificates pay a dividend A after the first period and a liquidation dividend B at the end of the second period. Both dividends depend on the **mutually independent realized states in Period A and Period B**. An attached package of information and record sheets will help determine the value to you of any decisions you might make. Your are not to reveal this information to anyone. It is your own private information.

The type of currency used in this market is francs. All trading and earnings will be in terms of francs. Each franc is worth 0.002 **dollars to you (i.e. 500 francs = 1 US$)**. Do not reveal this number to anyone. At the end of the experiment your francs will be converted to dollars at this rate, and you will be paid in dollars. Notice that the more francs you earn, the more dollars you earn.

Specific instructions

At the beginning of a year you will be given a number of certificates. The certificates will pay a dividend at the end of each period (as will be explained below). Your profits come from two sources - from collecting certificate dividends on all certificates you hold at the end of a period and from buying and selling certificates. During each market year you are free to purchase or sell as many certificates as you wish. For each certificate you hold at the end of a period you will be given a dividend depending on the realized state. You will find dividend values in a box at the top of your information and record sheet each year. For example, suppose your box looked like the one below:

	State	Dividend
Period A	H_A	8000
	L_A	9000
Period B	H_B	10000
	M_B	11000
	L_B	12000

For each certificate that you held at the end of Period A you would receive 8000 or 9000 depending upon whether the state in Period A was H_A or L_A. In addition, for each certificate you held at the end of Period B you would receive 10000, 11000 or 12000 depending upon whether the state in Period B was H_B, M_B or L_B.

Thus, you will start every odd period (Period A) with an initial endowment of 10 certificates. You may sell these if you wish, you may hold them, or you may buy more. If you hold a certificate throughout both periods, then you receive both dividends A and B. Notice therefore that for each certificate you are given initially you can earn at least the sum of the two dividends (one for Period A and one for Period B) by simply holding and not selling them. Your initial holding at the beginning of Period B is determined by your final holdings in Period A, i.e. your certificates and cash are carried over from Period A to Period B.

At the end of a year you are free to keep all dividends plus your francs on hand minus 32000 francs. These are your profits for the year.

Determination of States

The dividend you receive from the certificates you hold depends on the states of the two periods:

- In **Period A** the state can be either $\mathbf{H_A}$ or $\mathbf{L_A}$.
- In **Period B** the state can either be $\mathbf{H_B}$, $\mathbf{M_B}$ or $\mathbf{L_B}$.

The states are associated with corresponding dividends as given in your Record Sheet. The states of both periods will be randomly and independently determined before each year begins. The state will be made public after the corresponding period. The random numbers were picked from a random number table, which can be inspected by anyone after the experiment.

Period A $\mathbf{H_A}$ dividends and **Period A** $\mathbf{L_A}$ dividends are equally likely (i.e. if you repeat this experiment over and over again, about one half of the time a $\mathbf{H_A}$ dividend would be paid and about one half of the time a $\mathbf{L_B}$ dividend would be paid.). In **Period B** state $\mathbf{H_B}$, state $\mathbf{M_B}$ and state $\mathbf{L_B}$ are all equally likely (i.e. if you repeat this experiment over and over again, state $\mathbf{H_B}$ would occur about one third of the time, state $\mathbf{M_B}$ would be realized about one third of the time and about one third of the time the $\mathbf{L_B}$ state would occur.).

Information about States

At the beginning of each year you pick a clue card out of a box. The clue card carries your private information, and you are not to reveal this information to anyone. It will be of the form:

Period A Dividend	Period B Dividend
___	**NOT ___**
	(i.e. either __ or __)

Suppose for example the Period A state is H_A and the Period B state is H_B. Then the following clue cards will be in the box:

Period A Dividend	Period B Dividend	Period B Dividend
$\underline{H_A}$	**NOT $\underline{M_B}$**	**NOT $\underline{L_B}$**
	(i.e. either L_B or H_B)	(i.e. either M_B or H_B)

One third of the people would draw the card on the left, one third would draw the card in the middle and, one third would draw the card on the right.

Information and Record Sheet

At the end of each period the dividend will be announced. You should record your period's dividend earnings. At the **end of each trading <u>year</u>** you must compute your total earnings. Since you have an initial endowment of no francs you just have to fill in your final (Period B) cash. Notice that you have to fill in a negative final cash if on net you are buying certificates. Finally you copy your Period A& B Earnings on the Final Payout form. If you want to keep a personal transactions record during a period, you might use the table on your record sheet.

Example

Consider again the example above. Suppose for example that you hold 5 certificates at the end of Period A of year 1 (line (2)). If in Period A state H_A is realized, your certificates will pay 8000 each (line (1)) and your total certificate dividends in Period A would be 5*8000 = 40000 (line (3)). Suppose now that you hold 3 certificates at the end of Period B of year 1 (line (5)) and have a final cash of -29000 (line (8)). If in Period B state M_B is realized, you will receive 11000 per certificate (line (4)) and your total certificate dividends in Period B would be 3*12000 = 36000 (line (6)).

Now you add lines (3) and (6) and write the result in line (7) [here: 40000 + 36000 = 76000]. You obtain your Period A&B Earnings by adding lines (7) and (8) [here:76000 + (-29000) = 47000].

Are there any questions?

B. Design Parameters

Table 7: Design: Bets

In this table all bet design parameters are displayed for each session. Payment at the *C*alifornia Institute of Technology was in US$ and at Universität *M*annheim in DM. The next column shows the number of participants (*# P*). In both, *Period A* and *Period B* participants could choose between a *high* and a *low* bet which differ on the positive and negative payment depending on the correctness of subjects' individual dividend predictions. $p_i^* = \frac{\text{false}_{\text{low}} - \text{false}_{\text{high}}}{(\text{correct}_{\text{high}} - \text{false}_{\text{high}}) - (\text{correct}_{\text{low}} - \text{false}_{\text{low}})}$ is the probability for which the prediction has the same expected value for both bets.

					Period A					Period B		
Session	Place	# P	*high* bet		*low* bet		p_i^*	*high* bet		*low* bet		p_i^*
			correct	false	correct	false	correct	false	correct	false	p_i^*	
9510281	C	12	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
9511041	C	12	0.50	-0.25	NA	NA	NA	0.50	-0.25	NA	NA	NA
9511091	C	15	0.60	-0.30	0.30	-0.10	0.40	0.40	-0.40	0.20	- 0.10	0.60
9511141	C	15	0.60	-0.30	0.30	-0.10	0.40	0.40	-0.40	0.20	- 0.10	0.60
9511161	C	15	0.60	-0.30	0.30	-0.10	0.40	0.40	-0.40	0.20	- 0.10	0.60
9511261	C	15	0.60	-0.30	0.30	-0.10	0.40	0.40	-0.40	0.20	- 0.10	0.60
9511271	C	15	0.60	-0.30	0.30	-0.10	0.40	0.40	-0.40	0.20	- 0.10	0.60
9511281	C	15	0.60	-0.30	0.30	-0.10	0.40	0.40	-0.40	0.20	- 0.10	0.60
9512111	M	10	0.50	-1.00	0.25	-0.25	0.75	0.50	-1.00	0.25	- 0.25	0.75
9512112	M	10	0.50	-1.00	0.25	-0.25	0.75	0.50	-1.00	0.25	- 0.25	0.75
9512121	M	12	0.60	-0.40	0.30	-0.10	0.50	0.40	-0.40	0.20	- 0.10	0.60
9512131	M	12	0.60	-0.40	0.30	-0.10	0.50	0.40	-0.40	0.20	- 0.10	0.60
9512141	M	12	0.60	-0.40	0.30	-0.10	0.50	0.40	-0.40	0.20	- 0.10	0.60
9512151	M	12	0.60	-0.40	0.30	-0.10	0.50	0.40	-0.40	0.20	- 0.10	0.60

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