Software Agents and Market (In)Efficiency - A Human Trader Experiment

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***Abstract*—This paper studies how software agents influence the market behavior of human traders. Software agents with a passive arbitrage seeking strategy are introduced in a double auction market experiment with human subjects in the laboratory. As a treatment variable, the influence of information on the existence of software agents is investigated. We found that common knowledge about the presence of software agents triggers more efficient market prices when the programmed strategy was employed whereas an effect of the information condition on behavioral variables could not be observed. When controlling for information on software agents' participation the introduction of software agents results in lower market efficiency.**

***Index Terms*—Artificial Trading Agent and Human Traders, Electronic Market, Double Auction, Experimental Economics**

I. Introduction

One exemplary application where humans and software agents participate alike is eBay [1]. The auction format used by eBay is an open bid second price auction with a fixed ending rule. In this situation bidders have a strategic incentive to delay their bids [2] and to bid at the very end of the auction, so-called sniping. Most of the bidders place their bid using eBay's graphical user interface. Lately services such as esnipe and auctionblitz[1] have offered to place a bid at the very last minute on the bidder's behalf. This automated bidding supports human bidders in a routine task that is thus performed more precisely. In this example, the software agent exploits human shortcomings (bidders not recognizing the strategic incentives of late bidding) and does the job without the proneness to error of human interaction with software systems.

In a different environment, we are posing the following questions that might be stated in the eBay context as well: How do software agents influence the market behavior of human traders? And does individual knowledge about software agents influence human behavior and the market outcome?

The intention of this study is to concentrate on a stylized, controlled environment and to understand and disentangle the economic and psychological drivers of human-agent interaction. We rely on a market institution quite common in financial markets - the continuous double auction (CDA). In this auction type sellers and buyers may submit bids and asks asynchronously and in continuous time. The framework that allows software agents to interact with such a market is described in Grossklags *et al*. [3], where a simulation exclusively with software agents was conducted.

In the present paper, human traders are introduced into this framework. In June 2001 we conducted first pilot experiments featuring the simultaneous participation of human traders and software agents to decide which agent trading strategy to select for the human-agent interaction experiment. We chose a natural, easy to interpret and financially relevant agent strategy to explore human-agent interaction. The *arbitrageur* constantly scans the market in order to exploit risk free profit opportunities, resulting from price variations of a contract in different markets. From a behavioral point of view, the arbitrageur can be described as a passive, rather parasitic strategy sitting in the background and earning profits from the imperfections of other traders. In the following sections, in order to distinguish human traders from software agents acting as traders as well, the term "traders" will be used for human participants and the term "agents" for software participants.

Closely related to our experiment, Das *et al*. [4] conducted an experimental series where human traders interacted with software agents. They followed the design proposed by Smith [5] where participants were assigned fixed roles as either buyer (submitting only bids) or seller (submitting only asks) and received a private valuation (cost) for the traded good as a buyer (seller). In their study the experimental conditions of supply and demand were held constant over several successive trading periods and were then exposed to a random shock that changed market parameters. Experimental sessions involved 6 human traders and 6 agents. In addition, a baseline session with 12 human traders was run. Two types of agents were used that applied either a modified Zero-Intelligence-Plus strategy [6], [7] or a modified Gjerstad-Dickhaut algorithm [8]. They note in their report that bidding strategies of the

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[1] www.esnipe.com, www.auctionblitz.com

employed agents were not discussed in detail with the human traders during the instructional phase. It appears, however, that human participants knew they competed with agents.

In general, human-agent markets show convergence to the predicted equilibrium and improved efficiency compared to a market with human traders only [4]. Agents reaped average profits well above those of human traders. Between 30 and 50 percent of the trades were done between agents and human traders.

Compared to Das *et al.* [4], the present paper introduces software agents into a more complex and natural trading environment. This includes the following: a trader acts both as a buyer and seller; information about the fundamental value of the securities changes in every round; orders allow for multiple units of a specific contract; and the market institution does not provide a spread improvement rule. Additionally, many other CDA experiments (e.g., [4]) rely on a single observation for each treatment. To add robustness to our results we collected six statistically independent observations for each treatment.

Our main contribution is the introduction of an information condition into a human-agent experiment. Two treatments were conducted with experimental parameters held constant except for the information available about the software agents: in one treatment the participation of the software agent was made common knowledge, and in the other treatment subjects were not informed about the existence of software agents. In addition, the data is compared to a third treatment (which we call baseline treatment) without software agents or information about the presence or absence of software agents.

We can formulate hypotheses with regards to the influence of software agents on human traders. Following the results of related work (e.g., [4]) we expect the arbitrage agent will improve market efficiency. The agent follows predefined rules and does not make mistakes with respect to its algorithm. In addition, the arbitrage agent can process more data in a given time span and interact faster with the software interface than human traders are able to interact with the graphical user interface.

More importantly, the introduction of the information condition allows us to form a central hypothesis about the reactions that can be expected from human traders when information on software agents is provided. Human traders suffer from the uncertainty about the agents' capabilities, e.g., their speed in calculating strategies and in processing transactions. This uncertainty might lead agents to crowd out humans from the market. It is a strong hypothesis that would require human traders not to trade at all when information about the existence of software agents is available. However, in the context of the double auction market institution, traders cannot observe if a particular trade is done with a human or a robot. Thus, an alternative hypothesis can be formulated according to which humans compare themselves with other human traders only and neglect the existence of software traders. This hypothesis would predict no difference in human behavior when information is provided.

We find that agents do not crowd out human traders in the treatment with common knowledge on software agents. Instead, common knowledge on the presence of software agents has a significantly positive effect on human traders' ability to converge to equilibrium in the presence of the arbitrageur agent. Furthermore, intuition would suggest a higher efficiency in an environment with software agents when compared to no software agents. Surprisingly, when compared to the baseline treatment the introduction of an arbitrage seeking type of software agent results in lower market efficiency in the no information treatment.

In Section II the experimental design is presented, including the market and the software agents' strategy. The experimental results are described in Section III. Related work is discussed in Section IV. In Section V we interpret and discuss our non-intuitive results. Section VI reproduces the experimental instructions used in the laboratory.

II. Experimental Design

A. Market Institution and Information

The market institution was designed by using a continuous double auction, i.e. an auction in which sellers and buyers may submit bids and asks simultaneously and asynchronously. More precisely, sellers and buyers are free to accept bids and asks at any time during the experiment. CDA market designs are very popular among financial markets, both real and virtual, and are described as having the remarkable quality of being fast and efficient [9], [10]. In contrast to markets where the issue of securities is organized by an initial public offering, this is implemented on this particular market via a so-called bundle mechanism and therefore resembles closely the design of the Iowa Electronic Markets [11], [12].[2] The bundle consisted of a standardized unit-portfolio where the sum of each different contract carries a fixed price. This bundle can be bought from or sold to the bank at any time and any quantity. Therefore, when the valuation of contracts in the market exceeds or falls below the fixed value of the bundle then there exists a situation of over- or undervaluation, respectively. In our experiment the fixed price of the bundle is set to 100 ECU (Experimental Currency Unit). The market foresaw three valid operations: (1) posting market orders (bids implement buying orders and asks implement selling orders), (2) deleting own market orders, and (3) buying/selling bundles at the bank. Submitted orders remained open until they were traded, they expired, or the experiment ended. No restrictions to the posted prices were made.

The market implements an American futures market, where contracts can be traded on some kind of event. The outcome of the event determines, depending on the market rules, the payoff of the different contracts. For the experiment described, a payoff scheme similar to "vote share" election markets has

[2] The market software for the experiment uses Web technology and has been used, for example, in Hansen et al. [13] and Schmidt and Werwatz [14].

been used, where each contract pays off a percentage of the total bundle. That is each contracts will be exchanged into ECU given its final fundamental value. The experiment was conducted with a market that contained five contracts each representing one firm. Three contracts represented relatively more valuable firms (contracts A, B, and C) and two representing relatively less valuable firms (contracts D and E).

The value of each different contract was characterized by a strength measure given in points. For example, if the firm is doing well it will gain points, whereas if it performs poorly it will lose points. Furthermore, the strength points provide an indicator of its relative performance compared to the other contracts in the bundle. This implies that an increase in points in one contract results in a proportional decrease of the equilibrium price of the other contracts on the market as well. The equilibrium price equals the fundamental value of a contract and can be calculated by dividing the points of a contract by the sum of points of all different contracts in the market multiplied by 100.

The instructions (available in the appendix) contain the following example to illustrate this process. Consider a point valuation of the contracts of A – 36 points, B – 26 points, C – 26 points, D – 12 points, and E – 10 points. Then the fundamental value of contract A can be determined as follows: Add the points of all stocks together (that is 110 Points). That means that currently 110 Points correspond to 100 ECU (that is the fixed bundle price). The contract A is then (36 points*100)/110 points = 32.7 ECU worth. Note that every deviation from this value that is observable in the market indicates an over- or undervaluation.

During the experiment, the participants received the information on their computer screens. Initially, all participants were given the same information in the instructions and a trading time of three minutes. Afterwards, the information was sent by the following schedule: reception of private information on the contracts' points, 4 minutes time of trading, reception of public information, and 2 minutes time of trading. This schedule was repeated 12 times. Altogether the market was open for 75 minutes and each subject received 13 public and 12 private information messages.

A storyboard was designed in order to provide a constant environment for all sessions and treatments. The exact point values for the five contracts (that are equal to the public information the traders received) are given in Table I. The corresponding fundamental values in ECU are reproduced in Table II. Figure 1 presents the equilibrium prices over time for each of the 5 contracts. Table III reports the private information given to subjects. The storyboard was determined by the experimenters with a rolling dice. The storyboard describes the change of points and the corresponding fundamental value of the five different contracts, and the private information points distributed to the six human traders' roles. Thus, each human trader role, say for example trader number 2, was assigned the same information

TABLE I
DEVELOPMENT OF POINT VALUES FOR EACH CONTRACT

Round[a]	A	B	C	D	E
0	26.0	26.0	26.0	12.0	10.0
1	**33.5**	26.0	26.0	12.0	10.0
2	33.5	26.0	26.0	12.0	**13.5**
3	33.5	26.0	**20.0**	12.0	13.5
4	33.5	26.0	20.0	**10.0**	13.5
5	**22.5**	26.0	20.0	10.0	13.5
6	22.5	26.0	**29.5**	10.0	13.5
7	**16.5**	26.0	29.5	10.0	13.5
8	16.5	26.0	29.5	10.0	**6.5**
9	16.5	26.0	29.5	**15.0**	6.5
10	16.5	26.0	29.5	**16.0**	6.5
11	16.5	26.0	29.5	16.0	**4.0**
12	16.5	**19.0**	29.5	16.0	4.0

[a]Highlighted are contracts for which private information is available. Round zero indicates starting values.

TABLE II
DEVELOPMENT OF FUNDAMENTAL VALUES FOR EACH CONTRACT

Round[a]	A	B	C	D	E
0	26.0	26.0	26.0	12.0	10.0
1	**31.2**	24.2	24.2	11.2	9.3
2	30.2	23.4	23.4	10.8	**12.2**
3	31.9	24.8	**19.0**	11.4	12.9
4	32.5	25.2	19.4	**9.7**	13.1
5	**24.5**	28.3	21.7	10.9	14.7
6	22.2	25.6	**29.1**	9.9	13.3
7	**17.3**	27.2	30.9	10.5	14.1
8	18.6	29.4	33.3	11.3	**7.3**
9	17.6	27.8	31.6	**16.0**	7.0
10	17.5	27.5	31.2	**16.9**	6.9
11	17.9	28.3	32.1	17.4	**4.3**
12	19.4	**22.4**	34.7	18.8	4.7

[a]Highlighted are contracts for which private information is available. Round zero indicates starting values.

TABLE III
PRIVATE INFORMATION GIVEN TO SUBJECTS (IN POINTS)

	Contract	Information streams (trader role)					
Round	changing	1	2	3	4	5	6
1	A	35.0	31.5	36.0	32.5	31.5	34.5
2	E	13.0	14.0	13.0	14.5	13.0	13.5
3	C	24.5	16.5	14.5	24.5	15.0	25.0
4	D	8.0	8.5	7.0	12.5	11.0	13.0
5	A	21.0	21.5	24.0	23.0	22.5	23.0
6	C	28.5	29.5	31.0	30.5	30.0	27.5
7	A	12.0	12.5	13.0	20.0	21.0	20.5
8	E	11.0	3.5	8.5	3.0	7.5	5.5
9	D	14.5	14.0	16.0	15.5	16.5	13.5
10	D	20.0	21.0	12.0	14.0	17.0	12.0
11	E	3.0	2.5	3.5	5.5	5.0	4.5
12	B	14.5	22.5	23.5	22.0	16.0	15.5

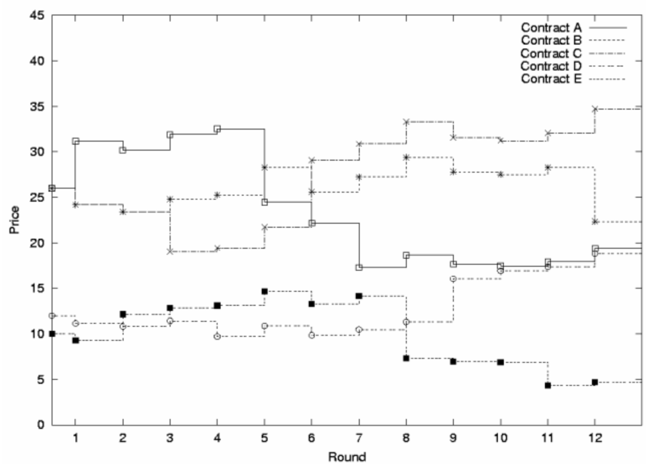

Fig. 1. Model of the fundamental value of each firm's contract.

throughout all sessions. For the sake of simplicity, only one contract changed its points in each round, so that if the points of contract A were going to change in the first round the other contracts didn't change in points. Still, this scenario implies a change of the fundamental value of all the different contracts in the market. Each of the six traders in this storyboard received different private information about the change in points. The mean of all private information sent to the traders was equal to the actual change. This true change was made available to the traders with the public information.

B. Programmed Trader

The market-agent interface (XML) and several implemented software agents (in Java) are described in detail in Grossklags *et al.* [3]. For the purpose of Grossklags *et al.* the software agents were selected under the premise of being pure and simple strategies, which resemble a real world analogy. A simulation tested the market-agent interface and pointed out strategies that are successful when competing with other software agents. For the present study we selected the *arbitrageur* agent because it is expected to be also profitable in a market experiment populated with human traders, and it employs a natural and financially relevant strategy. It is a software agent who constantly scans the market in order to exploit risk free profit opportunities, resulting from price variations of a contract in different markets. From a behavioral point of view, the *arbitrageur* can be described as having a passive, rather parasitic strategy sitting in the background and earning profits from the imperfection of other traders.

Arbitrageur: Aim of this agent is to profit from arbitrage opportunities that arise because of the difference between the market price and bank bundle price. In detail, the *arbitrageur* aims to profit from any difference between the market price of the contracts - more correctly, the bids and the asks of each single contract forming a bundle - and the bank price for the same bundle that is fixed. If a difference exists the agent is buying the bundle from whomever sells it at the lowest price (the bank or traders in the market) and reselling it to whoever is ready to buy it at the highest price (the bank or traders in the market). When the agent is able to conduct all transactions, in the experiment this includes at most 5 market transactions and one bank transaction, a guaranteed profit can be achieved.

The *arbitrageur* continuously scans the market and applies the following algorithm:

- if the sum of lowest selling offers for the five different contracts is below the fixed bundle price of 100 ECU, then buy the available unit-portfolios that fulfill this condition from the market and resell them to the bank as a bundle
- if any combination of contracts (one contract alone, two contracts, three contracts, etc.) is requested in the market at a price, which exceeds the fixed bundle price of 100 ECU, then buy a bundle from the bank, split the bundle and sell the contracts separately to the market.

The simulation in Grossklags *et al.* [3] displayed that in the sample environment with 11 different programmed strategies the *arbitrageur* was not in every case able to complete the whole set of transactions necessary in order to gain a sure profit and avoid risk. Still in the simulation the *arbitrageur* agent gained on average positive payoffs. In our experiment we did not observe any occasion where a software agent ended up with an incomplete set of transactions.

C. Experimental Procedure and Hypotheses

The experiment is designed to separate the influences of the programmed strategy and information on the participation of software agents. Therefore, the agent treatment has been run with and without information on software agents. In addition, a baseline treatment with human traders only has been run. For this treatment no information about software agents was given out.[3] Each session consisted of a market with 6 human participants and 6 streams of information. In the *arbitrageur* treatment the software agent was used in addition to the 6 human traders. The passive trading strategy *arbitrageur* does not use point information on individual contracts in order to apply its strategy (only market prices and quantities). Thus, we didn't provide the agent with point information, but all other information available on the market. Apart from the presence or absence of software agents and the provision of information about the existence of software agents there was no other difference between the individual markets. Altogether 18 sessions have been run with 108 *different* human participants and 12 programmed traders and thus six independent observations for each treatment were collected. That is we repeated every treatment six times with a new group of participants but under identical conditions, e.g., the same information condition. This enables us to run statistical test to compare the three treatments.

The human participants were recruited among students of the University of Jena, Germany. The laboratory sessions took

[3] Note that in contrast to experiments in psychology it is an enforced general standard in economic experiments not to lie to participants. Therefore, we have not conducted a treatment without agents while still providing information that software agents are present.

place in June 2002 in the experimental laboratory of the Max-Planck Institute for Research into Economic Systems. In the experiment software agents face the same budget constraint as human traders do. Each participant - traders as well as agents – was given an initial endowment of 100,000 ECU = 10 EURO. Participation lasted on average two hours. Payments were above opportunity costs. At the beginning of the experiment the instructions were available on the computer screen and read out loud by the experimenter (refer to the appendix for a translated version of the instructions). A demonstration of the trading screen including sample transactions for all three valid market operations was provided with a video projector.

Two hypotheses with regards to the influence of software agents on human traders were formulated. First, a crowding out of human traders might be predicted in the treatment with public information on software agents. This hypothesis predicts that human traders will not trade at all when information about the existence of software agents is available. However, in the context of the double auction market institution, traders cannot observe if a particular trade is done with a human or a robot. Thus, an alternative hypothesis can be formulated according to which humans compare themselves with other human traders only and neglect the existence of software traders. This hypothesis would predict no difference in human behavior when information is provided.

Second, software agents are expected to improve market efficiency (see, for example, [4]). They follow predefined rules and do not make mistakes with respect to their algorithm. In addition, software agents can process more data in a given time span and interact faster with the software interface than human traders are able to interact with the graphical user interface. For the evaluation of this hypothesis efficiency deviations from the equilibrium price and volatility measures of the different treatments are evaluated.

III. RESULTS

In a first step we compare the payoffs of human traders and software agents. We observe that software agents do not make losses (see Table IV). This is an important fact because the researcher would lose experimental control if agents just distribute money to human traders. A zero sum market has been used; therefore, each different agent should at least regain the invested capital of 100,000 ECU on average. Out of 12 sessions, agents achieved positive payoffs in 11 cases. One *arbitrageur* agent made a zero profit due to missing arbitrage opportunities. Profits of the agents differed significantly from zero (see Table IV): on average the *arbitrageur* agents made 0.3% profit during the 75 minutes period of time.

Human traders did lose this percentage in the corresponding treatments but this loss is not significantly different from zero profits ($T = -0.963$; $p < 0.33$). Furthermore, the variability of the software agents' profits is significantly lower when compared to human traders payoffs ($F = 3.596$; $P < 0.000$).

TABLE IV
AVERAGE PAYOFFS

	No Agent	No Information Arbitrageur	Information Arbitrageur
Software Agents	-	100,323**	100,282**
		(248.9)	(285.7)
Human traders	100,000	99,946	99,953
	(7,447.5)	(5,626.8)	(7,469.9)

* (**) [***] significant at the 10% (5%) [1%]-level, one-sided t-test, standard error in parenthesis.

TABLE V
NUMBER OF TRADES BETWEEN HUMANS AND BETWEEN HUMANS AND AGENTS

	Human-to-Human`	Human-to-Agent	Total
No Agent			
Session 1	126	-	126
Session 2	142	-	142
Session 3	128	-	128
Session 4	92	-	92
Session 5	177	-	177
Session 6	185	-	185
Average	141.7	-	141.7
Standard deviation	(34.8)	-	(34.8)
Arbitrageur - No Information			
Session 7	76	5	81
Session 8	82	15	97
Session 9	38	5	43
Session 10	217	27	244
Session 11	52	10	62
Session 12	82	40	122
Average	91.2	17.0	108.2
Standard deviation	(64.2)	(13.9)	(71.9)
Arbitrageur - Information			
Session 13	159	105	264
Session 14	73	0	73
Session 15	84	5	84
Session 16	117	35	117
Session 17	74	10	74
Session 18	103	5	103
Average	92.5	26.7	119.2
Standard deviation	(34.5)	(40.3)	(73.0)

Next, we analyze behavioral variables. In particular, we study the number of trades and portfolio restructuring activities of human traders and agents. We compare average values of the 6 independent observations for each treatment and if not otherwise noted we perform a permutation test in order to test for statistically significant differences. For both agent treatments the number of trades is not significantly different from the baseline treatment. The average number of trades declines in the *arbitrageur* treatment when compared to the baseline treatment but this effect is not significant. We attribute this finding to a high variability of the individual sessions' averages.

It can be observed that agent participation contributes to a decline of human-to-human transactions. The number of human-to-human transactions is significantly lower in the treatments involving a software agent when compared to the baseline treatment. The percentage of human-to-agent (h2a) trades in the *arbitrageur* regime is 16% in the no information and 22% in the information treatment, respectively (Table V).

On the individual level we observed 4 human traders, each of them in a different session, who did not trade at all (even though they had to stay for the complete experiment). This behavior could be observed twice in both the information and the no information treatment. Thus, a crowding out of human trades by the presence of information on software agents could not be confirmed and this hypothesis was not validated.

Result 1: *There is no crowding out of human traders when public information on software agents is available.*

In the following the focus of this paper will shift to explore several efficiency measures. In a first step arbitrage opportunities between the market and the bank are evaluated. The bank promises during the experiment to buy and to sell the unit portfolio for a fixed price of 100 ECU. Therefore, the aggregated price of one unit of each different contract on the market should be 100; lower market prices are an indicator for undervaluation, and higher market prices for overvaluation. The *arbitrageur* agent explicitly scans the market for immediate arbitrage opportunities. It can be suspected that the market price of a bundle should be close to 100 in this regime. Table VI provides evidence that on average in the *arbitrageur* regime as well as in the baseline treatment the unit portfolio is not significantly different from 100.

The information provided in the private information phases allows calculating the fundamental value of a contract from the six different pieces of information provided to the six human traders. During the public information every trader could directly compute the fundamental value from the point information contained in the message. Price deviations from equilibrium will be considered as inefficiencies. The efficiency measure is 1 when the market price equals the fundamental value. When contract prices are below fundamental value efficiency is calculated by dividing price by fundamental value. With contract prices above fundamental value efficiency is calculated dividing fundamental value by price.

Efficiency is lower in later periods what can be attributed to the increasing complexity of the information structure. It can be observed that the baseline and the *arbitrageur* no information treatments differ significantly from the *arbitrageur* information treatment (see Table VII). We conclude that the information condition has a significant effect on the human traders in case of the passive agent: human participants are observed to trade closer to equilibrium when informed about agents' presence.

Result 2: *Information condition: The public information on the presence of software agents has a significant positive effect on human traders' ability to converge to equilibrium in the presence of the arbitrageur agent.*

TABLE VI
UNIT PORTFOLIO OF MARKET PRICES[a]

	No Agent	No Information Arbitrageur	Information Arbitrageur
Overall	97.82	102.11	99.61
	(5.23)	(5.39)	(3.52)
Round 1-6	106.70	108.52	104.17
	(5.87)	(11.95)	(2.43)
Round 7-12	90.73	98.63	97.96
	(8.34)	(2.86)	(3.32)

[a]Average over six sessions, standard deviation in parenthesis.

TABLE VII
EFFICIENCY[a]

	No Agent	No Information Arbitrageur	Information Arbitrageur
Overall	0.82	0.75	0.81
	(0.13)	(0.20)	(0.16)
Round 1-6	0.85	0.81	0.83
	(0.12)	(0.18)	(0.16)
Round 7-12	0.78	0.70	0.78
	(0.13)	(0.20)	(0.15)

[a]Average over six sessions, standard deviation in parenthesis.

TABLE VIII
DETERMINANTS OF EFFICIENCY (RANDOM EFFECTS GLS-REGRESSION)

	Dependent Variable: Efficiency[a]		
Independent Variables	Model I	Model II	Model III
Constant	0.851***	0.854***	0.880***
	(0.017)	(0.012)	(0.018)
Arbitrageur, no information	-0.044*	-0.46**	
	(0.024)	(0.020)	
Arbitrageur, information	0.005		
	(0.024)		
Arbitrageur Agent			-0.044*
			(0.024)
Information			0.049**
			(0.024)
Round 7-12	-0.069***	-0.069***	-0.069***
	(0.000)	(0.000)	(0.000)
Wald chi2	108.75	109.14	108.75
R^2 (within)	0.0446	0.0446	0.0446
R^2 (between)	0.3069	0.3042	0.3069
R^2 (overall)	0.0719	0.0723	0.0719

* (**) [***] significant at the 10% (5%) [1%]-level, standard error in parenthesis.

[a]18 sessions as group variable (random effect), 2214 observations.

To further explore the determinants of non-equilibrium trade we ran a GLS regression using the complete data including the baseline treatment. Since deviations in each of the 18 sessions are likely to be correlated, and in a statistical sense are not strictly independent, an error components econometric model with the session as the random component is used. To explain efficiency the treatment variables and Round 7-12 are included in the regression. Significant positive signs imply trade closer to equilibrium. Table VIII reports the results.

Confirming our discussion on efficiency we find the arbitrageur information treatment not different from the baseline (Model I) and efficiency decreases significantly in the *arbitrageur* no information treatment (Model I,II). When controlling for information on the software agents' presence we find lower efficiency with respect to the introduction of the arbitrageur agent (Model III).

Result 3: *Baseline treatment: Surprisingly, the introduction of software agents results in lower market efficiency in the no information treatment when compared to the baseline treatment.*

IV. Related Work

A. Experimental markets involving agents and human traders

In the introduction of this paper we discussed the experimental results by Das et al. [4].

In [15] the authors developed algorithms that employ heuristic fuzzy rules and fuzzy reasoning mechanisms. In direct comparison to other benchmark algorithms (including those in [4]) they achieve superior performance. According to them, these results are particularly promising since the benchmark strategies have been shown to outperform human bidders (referring to the results in [4]). This is an exemplary conservative statement. We are confident that our research helps to increase understanding of the complexities of the interaction between human traders and software agents so that such generalizations and comparisons can be made with greater accuracy.

Byde *et al.* [16] use a laboratory experiment to study the interaction between a procurement negotiation and bidding agent and three human bidders. The authors comment on the question whether it is possible to identify the agent and whether the agent delivers adequate performance compared to human buyers. The experimenters informed human bidders that a software agent was participating in the negotiations. According to exit interviews, experiment participants were not able to identify the artificial trader. However, the results indicate that the automated trader is not always successful in achieving a good balance between total cost and target quantity purchased when human bidders are present.

The real-time experimental study reported in [17] sheds light on the interaction of human players and automated agents (that employ a selfish and myopic strategy) in a congested network. Players (human or artificial) are rewarded for downloading complete data packets but penalized for delay due to congestion. Human players were made aware about the agents' presence and informally notified about the approximate strategy of the agent. In their setting most players incur an overall loss and artificial players do significantly less well on average. Only in treatments with high capacity or large background noise agents compete successfully with human traders. Humans are observed to be slower and less able to exploit excess capacity whereas bots are capable of executing their strategy perfectly in those networks. However, agents' failure to internalize the difference between observed congestion and anticipated congestion stands in contrast to humans who react more flexible to changes in delay.

The results in [17] contribute to the more general discussion that agents based on statistical analysis of historical market data or static strategies may be insufficient for the efficient operation of markets (an observation made in [18]). For example, [19] discuss the requirement for agents to also possess forward-looking attention. In their paper they compare the performance of human agents and zero-intelligence agents [6] in a double auction market environment with large avoidable cost. They observe that efficiency and stability are undermined in markets with human traders, however, markets populated with zero-intelligence traders perform even less satisfactory.

The authors in [20] report preliminary results of experiments investigating the interaction of inexperienced human traders with software agents on a futures market (see [21] for details about the used market). Statistical analyses are not reported, however, the authors describe their experiences qualitatively. They observe remarkable differences between the behavior of human traders and software agents. Besides simple technical analysis humans also aim to predict long-term market movements and conceive a strategy based on impression. In their experiment agents have outperformed humans on average. However, they conclude that this result depends on many aspects such as the spot data used and human trader strategies.

Providing a more complex setting, another experiment [22] studies human and artificial players in a business game with procurement, manufacturing and sales decisions. Six software agents using different strategies (random, simple prediction rules, and human trader strategies that were observed earlier) compete with four human traders. It is not possible to draw detailed conclusions from their reported data. They note, however, that one human trader dominates the population in total earnings, whereas the other humans perform on average worse than the software agents.

We also want to point the reader to a detailed review article [23] that offers a comprehensive discussion of the empirical validity of agent-based modeling approaches in terms of explaining data from experiments with human players.

Our paper presents an extended version of research results on the interaction of human traders and a simple arbitrage agent on a continuous double auction market [24]. In comparison to [24] we sharpened our results and explanations of the experimental observations. To enable replication of our experiment and to facilitate understanding this version also includes a more detailed description of the experimental setup including instructions, and descriptions of the storyboard, and the arbitrage agent algorithm. To improve the reader's ability to put our work in context we have also greatly extended our discussion of related work with special focus on experiments that combine human traders and software agents in market environments.

B. Research in experimental economics

Related research into experimental asset markets is vast in its dimensions and we will review only few results. Common to most market experiments is the incorporation of public as well as private information characteristics, for example, in Copeland and Friedman [25], Forsythe and Lundholm [26], and Plott and Sunder [27]. In these experiments, trade is motivated by differences in both private information and private valuations. Further, Smith *et al.* [28] and Peterson [29] have undertaken pure common value markets. In these cases, traders are endowed with only public and no private information regarding the expected common value. In these markets occurring trades are attributed to factors such as different risk attitudes and other unobservable characteristics of the traders (e.g., differences in individual price forecasts, accuracy of decision making due to experience or bounded rationality, and varying expectations concerning the other traders' strategies). See [30] for a comprehensive review of market experiments.

In the following we briefly present experiments that use programmed strategies in their setup. There are various reasons that can motivate experimenters to replace certain human player roles with artificial agents. For example, a researcher might only be interested in buyer or seller behavior or human subjects' responses to certain strategies.

A rare example that enables the comparison of experimental results using such an approach with a study relying on markets conducted with human subjects alone can be found in [31] (whose authors contrast [32] with [33]). Both, [32] and [33], present experimental results on natural monopoly markets with similar setups. However, only [32] utilizes computer-simulated buyer behavior. They find considerable use of monopoly power relative to [33]. The authors of [31] are undecided whether they should attribute this difference to the use of simulated buyers or possible differences in the subject pool (e.g., market experience of participants).

Three classical experiments that have pioneered the use of simulated traders are: [34] with results of a Cournot quantity variation duopoly game where single human subjects are matched with two simulated players; [35] which studies cooperation of human subjects in a bifurcated duopoly game where they are faced with automated players that either cooperate or defect, and [36] with a discussion of duopoly games in which an artificial player was either paired with a single human subjects or a group of three subjects.

A very interesting test of human responsiveness to mixed strategy play by a programmed player in a game with a unique mixed strategy equilibrium is presented in [37]. It reveals a widespread heterogeneity in the subject pool with respect to behavior and performance. On average subjects adjust surprisingly well to changes in the mixed strategy of the agent and reap profits above the Nash equilibrium level. The authors also present a simple model that explains the heterogeneity of the subject pool with a process of dynamic random belief formation.

C. Agent Tournaments

Tournaments present a straightforward way to compare agents' performance in a fair environment. In the artificial intelligence community agent tournaments are conducted in an increasingly complex environment, see for example, the Trading Auction Competition (TAC) described by Wellman *et al.* [38], [39]. In the 2001 TAC agents arranged in groups of eight are assigned the role of travel agents charged with the task of arranging and automatically shopping for trips. The challenging part for agents' design is to address the interdependence of the tasks necessary to complete a trip, and the ability to reason about others' strategies in a thin market of automated agents and in a continuous timeframe.

In experimental economics community work on programmed strategies has also been done by conducting tournaments [40] – [42]. Rust *et al.* [41] report on the Santa Fe Double Auction tournament, where researchers were invited to submit software agents that compete on a CDA market against one another. The most successful strategy in this tournament can be described as rather parasitic sitting in the background and exploiting the strategies of other agents. In addition, they report about an evolutionary tournament, where the percentage of agents was adjusted in accordance to the success of a strategy over time. Parallel to the tournament there has been a discussion on the lower bound of trading agents' intelligence to act similarly to human traders in a market institution [6], [7], [18], [19], [43].

D. Electronic Commerce

A good starting point on agent mediated electronic commerce can be found in Guttman *et al.* [44]. Hereafter, we focus on related work that is concerned about automated negotiation and bidding. In particular market-based approaches are reviewed, which provide a market institution and a set of rules to do the negotiation or bidding. In this context software agents act in a competitive environment, yet there are other approaches in the AI community, such as collaborative agents, that will not be reviewed here.

Authors in [45] introduce a sophisticated formal model for many-parties, many-issues and single-encounter negotiation. The authors note that from their complex model alone it is difficult to predict which negotiation strategy will be successful in certain contextual situations. To respond to these concerns they include a simulation study to investigate the behavior and interdependencies of the basic elements and parameters in their model.

Sim and Choi [46] focus on negotiation strategies enabling agents to be responsive to market conditions that are subject to frequent change. In particular, the authors search for workable solutions to deal with varying levels of initial disagreement (measured by the bid-ask spread) between buyers and sellers in a market with a changing number of available trading partners. Agents respond to initial offers by making a series of concessions that depend on the importance that a deal is closed, timing and competition. A different approach on automated concession making that is motivated by evolutionary computation is presented in [47]. The authors propose the use of a genetic algorithm that varies offers based on its perception of opponents' preferences, timing, the magnitude of initial bids and asks and the difficulty to agree on pricing.

The discussion of related work in [48] offers a good review of currently available commercial bidding tools as well as academic research on automated auction bidding.

E. Other fields

Obvious examples where both human traders and software agents participate are to be found in financial markets. In the early '90s neural networks, genetic algorithms, fuzzy logics, chaos theory, and other approaches were applied to automate trading. It seems the hype has disappeared, and "black box" traders are managing rather small funds on Wall Street. The majority of funds are now managed by human traders that are supported by software aids filtering and aggregating information.[4] This can also be attributed to still open research questions about the impact of artificial traders in situations of market instability. Exemplary, Leland and Rubinstein [49] and Varian [50] discussed the role of artificial traders that followed 'price insensitive' strategies such as portfolio insurance that might have contributed to the 1987 stock market crash. Gennotte and Leland [51] provide a rational expectations model that draws on these experiences and aim to explain financial instability and discontinuities.

Representative for the expanding field of theoretical agent-based computational finance Lettau [52] investigates how closely evolutionary (genetic algorithm) techniques can achieve the optimum in a purchase situation for a risky asset. Other early applications for evolutionary techniques are a genetic algorithm environment for learning to construct a test for general equilibrium in a foreign exchange market scenario [53], and a learning algorithm [54] that addresses investors' optimal choice in a repeated one-shot decision situation for a portfolio when costly information signals are available. Equally relevant approaches using neuronal network based agents as in Beltratti *et al*. [55] can find valuable applications in decentralized price-finding institutions. A further starting-point for agent design can be found in the economic mechanism design literature, see Varian [56] for an introduction to this discipline.

[4] See, for example, articles by Davidson, C. (1999) Securities Industry News, Vol. 11: "The Black Box: For Better or for Worse?" (May 24), "Military Technologists Aim Their Software At the Markets" (March 8) and "Still fuzzy after all these years" (June 14).

V. Discussion and Concluding Remarks

This paper reports on an experiment where human subjects and software agents participate in a double auction market simultaneously. In this environment traders can buy and sell American futures. The design of the experiment disentangled the effects of the introduction of software agents and the psychological effect of the public announcement about their presence. We conducted the experiment in a controlled laboratory environment, and collected six statistically independent observations for each treatment.

The first result is that human traders are not crowded out when the participation of software agents is made public. With respect to this result we find it useful to comment on the following questions: What are the incentives to trade in our experiment? Why do participants trade when they know that they compete against a software agent with unknown trading strategy?

Note that all human traders in the market know that their private information only indicates the trend the value of the stock will take and that other market participants receive similar information. Thus, the private signal and the subsequent true (public) information that is distributed to the traders do not give informational advantages to any trader. Under these conditions traders that are strictly risk averse and rational should refrain from any trading activity (and risk neutral traders would be indifferent between trading at the fundamental market value and avoiding to trade). Similarly one can argue that when traders are risk averse and already endowed with an ex ante Pareto-optimal allocation the receipt of information cannot create incentives to trade. This observation follows from the Milgrom-Stokey no-trade theorem [57]. The initial endowments that traders receive in our setup represent a Pareto-optimal allocation.

Our experimental results and those of others (e.g., [28], [29]), however, indicate that trades frequently occur in conditions that predict no trades. In the academic literature these observations are usually attributed to deviations from perfect rationality. For example, if traders question the rationality of other market participants (see, for example, [58]) they might be uncertain that future prices are aligned with fundamental values perfectly. Then traders might speculate in the belief that positive earnings from trade are achievable [28]. Under this theory a trader's belief of other traders' limited rationality can be sufficient to motivate trade. We want to note that experimental results generally show that even if participants depart from their optimal strategy they generally have a good understanding of the experimental structure and do not appear to act unreasonably (or truly irrational) [59].

However, [60] find that subjects might also trade in situations where speculation is not possible and transactions are not in their best interest. They attribute this observation to subjects' irrational desire to actively participate in the experiment. Our experimental setup does not allow differentiating between these two hypotheses. Therefore, we consider trades to be the result of a combination of violations of common knowledge of rationality and participants' desire to trade.

To our surprise human traders did not shy away from trading when they were informed about the presence of a software agent. We expected that common characteristics attributed to automated trading such as increased speed and perfect bidding accuracy would be a driver for human traders' individual rationality. However, the total number of trades is statistically indistinguishable in all three treatments. Human traders continue to search for speculation opportunities even when automated trading is introduced. Furthermore, the existence of a software agent with an unknown strategy might boost curiosity and subjects' willingness to participate in a potentially less favorable environment.

We also find a significant decrease of human-to-human trades in the treatments including an *arbitrageur* when compared to the baseline treatment. Thus, the software agent takes market share from human-to-human interactions rather than generating additional trading through its presence. We attribute this to the agent's passive (and parasitic) strategy, and expect a different effect when more active strategies are employed.

The second set of our results concerns informational efficiency. In our experimental setup we can measure efficiency as the deviation of market prices from fundamental values. We find that public information on the presence of software agents has a significantly positive effect on human traders' ability to converge to equilibrium in the presence of the *arbitrageur* agent. Surprisingly, the introduction of software agents results in lower market efficiency in the no information treatment when compared to the baseline treatment. In the following we discuss these results briefly.

The agent by quickly eliminating over- and undervaluation in the market (compared to the bank's fixed valuation) is reducing the number of available strategies to the humans and hence lowers the number of human-to-human trades. However, only human-to-human trades carry the ability to aggregate private information, and so the reduced trading results in higher average deviation from fundamental values and slower convergence. But when the presence of a software agent is known to the human participants their trading appears to be more conservative and closer to the fundamental values. This results in higher average market efficiency. It is straightforward to see that such adjustment is very unlikely if information about the agent is hidden and detection of the agent is difficult due to its passive and inconspicuous strategy. Further, we observe that increased caution dominates the effect of reduced human-to-human trading volume.

Our research's focus is to shed light on economic and psychological effects imposed on human beings when interacting with software agents in a competitive environment. The first studies conducted are to serve as a starting point to obtain a deeper insight in how to apply technically well studied software agents in an environment with bounded rational human beings. On a methodological level we are concerned with the rather high variability of individual session averages for efficiency and behavioral variables observed in this and other market experiments.

We feel confident that our design and the statistical analysis using the permutation test and random effects GLS regressions provide a good description of the underlying effects. Evidence on CDA markets relying on a single independent observation for each treatment should be treated carefully and may require further repetitions.

It can be observed that behavioral and economic effects can be attributed to different experimental conditions. With respect to the information condition human traders are observed to act more efficiently in a market environment when information on software agents is available. This might be the most surprising result of the study since standard economic theory would predict no treatment effects. To generalize the results, the introduction of different types of agents in the current framework might be interesting. Further, it seems that commodity auction experiments with human traders and artificial agents might be a promising area of research as well. Our results are important because they demonstrate the complexity of interaction between human traders that are subject to their innate bounded rationality and software agents that accurately but also pigheadedly follow a preprogrammed algorithm. While it appears possible to develop agents that on average outperform human traders in several situations (see, for example, the results reported in [4] or the positive payoff of the software agents in our experiment) more research is needed to guarantee the stability of such results and to explore unexpected effects of interaction. Furthermore, it is known that interactions between human traders and software agents already occur on financial markets and commodity trading platforms. However, the nature of these interactions is widely unstudied and uncontrolled. We advocate controlled laboratory experiments as an opportunity for researchers to evaluate the performance of agent algorithms and the robustness of market parameters (e.g., informational or allocative efficiency). Our contribution to this young field of research indicates the significance of such an approach and can help to stimulate further experiments.

Appendix – Experimental Instructions

Dear students,

Thank you for taking the time to participate in the experiment. Before we proceed with the experiment please turn off your cellular phone.

What is this experiment about?

We would like you to trade on an electronic market. In order to trade you will be provided with an initial endowment of 10 € = 100.000 ECU (Experimental Currency Unit). This is equal for each participant.

How is the experiment organized?

Each participant will receive at first information about the initial value of each stock (in Points). During the course of the experiment each participant will receive updates about the development of the value of the stocks. The experiment is divided in 12 Rounds. Each Round is structured as follows:

Step 1. Receive private information
Step 2. Four minutes for trading
Step 3. Receive public information
Step 4. Two minutes for trading

How do you trade?

In this market five different stocks can be traded. These stocks represent 5 companies. Thereof stocks of 3 companies have initial values that are relatively high (stock A, B and C). The stocks of the other 2 companies are initially valued lower in comparison (stock D and E). Stocks can be bought from and sold to:

a. The other participants of the market separately or,
b. The Bank as a bundle.

Each bundle consists of exactly one unit of stock of each firm (unit portfolio). Thus, in this experiment a bundle is formed through the combination of one stock of companies A, B, C, D and E each. This bundle can be bought from and sold to the bank any time during the experiment.

Value of a stock

The value of each stock is characterized by:

a. Points, that indicate the valuation of a company relative to the other companies in the market
b. Monetary value of a stock on the market, which is given in ECU

Initial value of the stocks:

Stock A	26 Points	=	26 ECU
Stock B	26 Points	=	26 ECU
Stock C	26 Points	=	26 ECU
Stock D	12 Points	=	12 ECU
Stock E	10 Points	=	10 ECU
Sum	100 Points		100 ECU

Warning: After the first information has been broadcasted, 1 Point is not equal to 1 ECU anymore!

The information

You will receive in turns two different types of information about the valuation of the companies: private information (that every participant receives confidentially) and public information. This process is the same for all traders. Your private information will not be 100% accurate but generally indicates the trend the points of a stock will take. The public information that follows will reveal the "true" change in the valuation of a stock. The public information is identical for every participant and is sent to everybody at the same time.

During the experiment you will automatically receive information (Points) on your computer screen, that will indicate changes in the valuation of the companies. For example, an increase in the number of Points of a company represents a positive shift in the company's valuation. However, an increase of the Points for a company does not necessarily mean that the price of the corresponding stock will rise by 1 ECU. A change in points will lead to a change of the weighting of the stocks in the bundle of stocks. The change of the weight of the stocks in the bundle will determine the value of the stocks.

*Example: Stock A has initially 26 Points. You receive the private information: "PRIVATE INFORMATION: last known valuation (in Points) of all companies A – 26, B – 26, C – 26, D – 12, E – 10; new private information is a change for stock A of + 10 Points". This means that according to your information stock A has now 36 Points. Now you can calculate the valuation in ECU of Stock A that corresponds to this information if you apply the following method: Add the Points of all stocks together (according to your private information that is 110 Points). That means that currently 110 Points correspond to 100 ECU (that is the price of a complete bundle that the bank is ready to buy and sell at all times). Your information therefore indicates that stock A is (36Points*100)/110 Points = 32.7 ECU worth. After a few minutes you receive the public information "PUBLIC INFORMATION: last known valuation (in Points) of all companies is A - 26, B - 26, C - 26, D - 12, E – 10; stock A has changed in value by +5". Every trader has now the information that stock A has a valuation of 31 Points. You may find the "true" corresponding market value of stock A by applying the method introduced above (31Points*100/105=29.5 ECU).*

What kind of help will the software provide you?

Please refer to the link "Help" on the screen (top left corner of the computer screen).

Participation of an Automated Trader

In this experiment an automated trader is participating. This "programmed trader" is informed as well as all human experiment participants.

Payoff rules

At the end of the experiment your total earnings are the sum of your liquid funds and the value of your stock holdings. The value of your stock holdings will be determined in the same way as demonstrated in the example above. That is, the final Points of a stock are multiplied by 100 and divided by the sum of Points of all stocks. Finally, to determine your monetary payment in € please divide your total experimental earnings (measured in ECU) by 10000. You will be paid in cash.

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