

HUMANS VERSUS AGENTS: COMPETITION IN FINANCIAL MARKETS OF THE 21ST CENTURY

Research-in-Progress

Shuo Sarah Zhang

Karlsruhe Institute of Technology
Kaiserstr. 12, Bldg. 01.80,
76131 Karlsruhe, Germany
sarah.zhang@kit.edu

Marc T. P. Adam

Karlsruhe Institute of Technology
Kaiserstr. 12, Bldg. 01.80,
76131 Karlsruhe, Germany
marc.adam@kit.edu

Christof Weinhardt

Karlsruhe Institute of Technology
Kaiserstr. 12, Bldg. 01.80,
76131 Karlsruhe, Germany
christof.weinhardt@kit.edu

Abstract

Information systems have revolutionized the nature of markets. Traditionally, markets inherently comprised the strategic interaction of human traders only. Nowadays, however, automated trading agents are responsible for at least 60% of the US trading volume on financial stock markets. In this respect, financial markets of the 21st century are different to markets of previous centuries. Fuelled by discussions on their possible risks, there is a need for research on the effects of automated trading agents on market efficiency and on human traders. In order to systematically investigate these issues, we introduce a market framework for human-computer interaction. This framework is then applied in a case study on a financial market scenario. In particular, we plan to conduct a NeuroIS experiment in which we analyze overall market efficiency as well as the trading behavior and emotional responses of human traders when they interact with computerized trading agents.

Keywords: Experiments, NeuroIS, Electronic markets, Human-Computer Interaction, Auction, Framework

Introduction

With the growing importance of algorithmic trading and high-frequency trading (HFT), more and more computer agents are being used in financial securities trading. Fuelled by discussions on the systemic risks that these kinds of trading participants might pose to financial markets, more research is needed that analyzes the effects of automated computer agents on market efficiency. A challenging aspect for empirical research is the gradual automation in financial markets and thus the impossibility of a clean separation of a world with and without computerized agents. In this article, we focus on the questions: (1) whether the interaction of human traders with computer agents has a systematic influence on their emotions and behavior, and (2) whether this in turn has an impact on overall market efficiency. In order to study this real-world phenomenon and to analyze a world with and without computer agents, we propose a laboratory experiment. Our contribution is twofold: Firstly, we present a market framework for human-computer interaction. Structured along this framework, we intend to give guidelines for studies involving human traders and computer agents in an experimental laboratory setting using NeuroIS tools. Secondly, we derive hypotheses from the market framework for human-computer interaction regarding differences in emotional reaction, trading behavior, and market efficiency for different participant and market settings. Moreover, we plan to conduct a financial market lab experiment in order to test these hypotheses. The specific hypotheses aim at: (1) whether humans act differently against computer agents than against other human individuals, (2) whether the interaction with computer agents leads to a different level of arousal, and (3) whether this eventually leads to differences in market efficiency.

Financial markets have significantly changed within the last decades. Financial markets in the 20th century have already brought geographically dispersed buyers and sellers of goods together. However, the 21st century has introduced a new type of electronic market where factors such as technology, speed, and the sophistication of computer algorithms have become vital for economic success. In today's electronic markets, computer agents are deployed for different purposes with different degrees of sophistication. On one side, there is sophisticated technology that is user-optimized and enhances efficiency and creativity. Examples for financial markets are classic "slice-and-dice" algorithmic trading agents. These agents are designed to receive human orders and slice them into smaller orders in order to minimize transaction costs and hide trading intentions. In a broader context of decision support, this group also includes information systems that reduce the decision complexity for users and learn their preferences and needs. Prominent examples are online recommendation systems that have been studied in recent NeuroIS literature (cf. Benbasat et al. 2010). On the other side, there are intelligent systems that are able to take over simple or even complex human tasks since they offer a higher degree of reliability and speed. As in the case of HFT, trading algorithms are able to make autonomous trading decisions within the blink of an eye and have gained a considerable amount of the total trading volume (for 2009: 61% of the trading volume in the US; purchases and sales, double-counted, cf. Tabb et al. 2009). This has led to a growing concern about whether HFT have a negative effect on market quality. At this stage, there is only little research on whether the presence of computer agents has direct effects on human trading behavior.

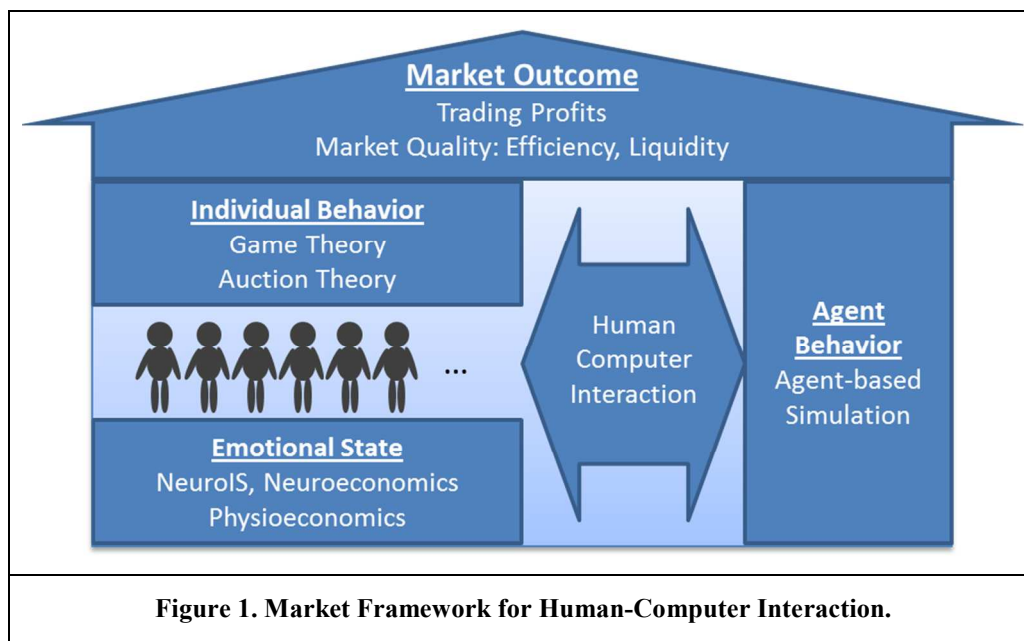
We contribute to existing IS literature by adding a focus on the interaction of human traders with computer agents in a competitive environment. Thereby, we follow a NeuroIS approach by applying psychophysiological measurements in a financial market lab experiment. By applying methodologies from neurophysiology and psychophysiology to information systems research, the new field of NeuroIS provides long overdue insight into the decision-making process of human individuals when interacting with modern information technology (Dimoka et al., 2012). The market design is outlined in the spirit of Gode and Sunder (1993) who conducted experiments with human participants and computer agents separately. Measures of efficiency include the deviation from the equilibrium price and the speed of convergence to market equilibrium. With our results, we intend to contribute to current discussions on HFT and its supposedly negative influence on the financial industry. Our case study represents a prominent example for the increasing amount of automated agents that are rather designed to compete with human traders than to facilitate human tasks. The remainder of the paper is organized as follows. In the section "Methodological Framework and Related Work," we describe the methodological framework that is derived from NeuroIS tools and present related studies in the fields of NeuroIS, human-computer interaction (HCI), and experimental economics. The section "Case Study" presents the market design and the current progress of the presented case study. The section "Conclusion and Further Research Agenda" concludes presents further extensions of the framework.

Methodological Framework and Related Work

Our case study combines research of several IS domains, such as NeuroIS, HCI, and economics of IS. The primary fields of study are depicted in the market framework for human-computer interaction in Figure 1. We first discuss the domains with regard to their relevance in the framework and then discuss further related work in each domain in more detail. Finally, we present implications and guidelines for the market design of an experiment to test hypotheses derived from the market framework for human-computer interaction as well as limitations of the framework. In our case study in Section 3, we present an application of this framework.

A Market Framework for Human-Computer Interaction

Following the research agenda for NeuroIS as described by Dimoka et al. (2012), we propose a framework that applies a NeuroIS approach for analyzing competitive human-computer interaction in large-scale double auction experiments. The framework is depicted in Figure 1.



The left hand side of the framework concentrates on human individuals' strategy and emotional state. Human behavior can be modeled with a game theoretical approach. In the context of financial markets, strategic actions involve the submission of a buy or sell order for a specific quantity and price and at a specific time. The interrelationship of emotional state and strategic behavior plays a vital role in human decision making. Studies on the emotional state are done extensively in the field of NeuroIS (Riedl et al., 2010a; Dimoka et al., 2011; Adam et al. *forthcoming*). Adam et al. (2011b) introduced a conceptual "framework for emotional bidding" in which the bidding behavior of individuals in auctions is directly influenced by the emotional state they are in. The emotional state can again be influenced by preceding auction outcomes which induces emotional reactions such as regret or joy. For the application to the human-computer interaction context, we assume that knowledge of the existence of computer opponents as compared to human opponents leads to a different level of arousal and subsequently to a behavioral bias in trading decisions.

The right hand side of the framework represents the agent behavior that is basically defined by the agent algorithms chosen. Research on artificial intelligence has been an important area of agent-based computational economics and has so far mainly concentrated on agent interaction. Only recently, the

competitive interaction of humans and computer agents has started to gain considerable attention (cf. De Luca et al., 2011; Riedl et al., 2011).

Interaction of humans and computer interfaces is a subfield of the research area HCI. Traditional HCI research concentrates on the support of computer systems for human tasks and the design of user interfaces. Research in this area will gain more attention in the future since we are interacting mainly with supportive computer systems in our everyday life, but also begin to compete with computer agents for specific tasks. As described in the introduction, we distinguish between supportive computer systems and competitive computer agents that are sophisticated enough to overtake simple or even complex human tasks. The focus in our framework is on competitive market environments and, thus, we also concentrate on competitive computer agents.

Market outcome is depicted in the upper part of Figure 1. Market outcome can be characterized by (1) overall market quality measures, such as market liquidity and market efficiency (Zhang et al., 2011), and (2) individuals' success measures, such as trading profits. Work in mechanism design analyzes the effect of different market mechanisms on human and agent behavior and its subsequent effect on market outcome. The interaction of strategic behavior and mechanism design is further analyzed in the field of auction theory. A common market mechanism in financial markets is the double auction. Double auctions are a market mechanism in which buyers as well as sellers are able to submit buy orders (bids) and sell orders (offers) and accept bids and offers simultaneously.

Individual Behavior and Emotional State

NeuroIS is a relatively new field in IS research and the use cases for NeuroIS research have grown considerably. NeuroIS is defined as the application of “cognitive neuroscience theories, methods, and tools in Information Systems (IS) research” (cf. Dimoka et al. 2007). It further understands itself as a “subfield in the IS literature that relies on neuroscience and neurophysiological theories and tools to better understand the development, use, and impact of information technologies (IT)” (cf. Riedl et al. 2010). The neuro- and psychophysiological tools include functional magnetic resonance imaging (fMRI), electroencephalography (EEG), electrocardiography (ECG), facial electromyography (EMG), and skin conductance response (SCR). Examples for IS research issues that can be tackled with NeuroIS methods include the identification of the TAM in the brain (cf. Dimoka and Davis, 2008) and the interaction of humans with recommendation avatars of different races and gender (cf. Dimoka et al., 2009; Riedl et al., 2011). Dimoka et al. (2012) outlined further research directions, some of them described below. In their recent work, Riedl et al. (2012) also addressed possible negative effects of technology usage using NeuroIS tools, such as the increase in “Technostress,” as measured by the increase of cortisol. Another instance of an increasing amount of stress is auction fever which has been analyzed by Adam et al. (2011a). A model for a more general emotion in competitive situations, “competitive arousal,” is introduced by Ku et al. (2005). Adam et al. (2011b) further introduced a methodological framework which is closely related to the psychophysiological tools in NeuroIS with a primary focus on economic problems, called “Physioeconomics.” Physioeconomics extends existing methods of experimental economics by measuring autonomic nervous system activity using well-established psychophysiological methodology. In the context of electronic markets, these measures can serve as proxies for the emotional processing of human traders. This methodology is also applied in our case study.

Application to IS Constructs: Human-Computer Interaction

Possible IS constructs for the analysis with NeuroIS methods have been outlined by Dimoka et al. (2011), with a focus on HCI constructs. A popular research focus is the construct of trust in HCI and its impact on behavior and neurology (e.g. Riedl et al. 2011, Dimoka 2010). This line of research is based on the assumption that computer agents are supportive for humans. Their results might have an unforeseeable impact not only on the form of communication in the future (with respect to avatar-based communication for example), but also on the visualization of information systems in general, such as avatar-based recommendation systems as studied by Al-Natour et al. (2006) and Benbasat et al. (2010).

In contrast to the supportive nature of agents, our research focus is the IS construct “competition” (cf. Dimoka et al. 2011). The group of competitive agents has a different nature than those related to supportive agents. In contrast to the “positive” construct of trust presented above, competition has a

rather negative connotation. As described by Smith (1776), competition is created by a shortfall of a specific commodity. While HCI literature has traditionally concentrated on supportive computer systems and the design of these systems, HCI literature on competitive interaction has been relatively sparse. Williams and Clippinger (2002) analyzed aggressiveness of human players in computer games. They found that users experienced higher levels of aggressiveness when playing with computer opponents than with a human stranger face-to-face. Decety et al. (2004) used neurological tools to shed more light on the visceral processes underlying competition in human-human interaction. The authors have understood competition as a “socially rewarding process” in the human-human context. Competitive human-computer interaction and its neurological impact have been further studied by Gallagher et al. (2002) and Sanfey et al. (2003). Recent studies have shown that the human opponents caused more activation with unfair offers in the ultimatum game (Güth et al. 1982) than computer opponents. This again can lead to a higher competition towards human opponents due to a social effect. With the growing sophistication of algorithms, trading agents have gained more abilities to learn and adapt their behavior to the economic and social environment. We argue that this kind of smart agents might have different effects on humans since interacting with computer intelligence might have a vital influence on the behavior and emotional state of human participants.

An increasing use of computer agents can also be observed in our everyday life. An example is the use of bidding agents on market platforms such as eBay, called “snipers” (Ariely et al., 2005). Snipers are programmed to make bids within the last seconds of an eBay auction. Assuming that there are no problems with the transfer of the bids, sniping is a weakly dominant strategy on eBay. This application might also raise concern about the fairness to other human bidders.

Market Outcome and Market Design

The analysis of strategic interaction in a competitive environment can be traced back to the introduction of game theory by von Neumann (1928). One assumption for game theoretic analysis is the notion of rational decision makers in the game. The rational expectation model understands expectations as informed predictions of future events and, thus, essentially the same as the predictions of the relevant economic theory (Muth, 1961). This notion has served as a foundation for auction theory and mechanism design. Based on the assumption of rational agents, the field of auction theory studies the design of market mechanisms and the quality of the market outcome. In recent economic literature, experimental economists have departed from the assumptions of rational agents in the rational expectation model (Camerer, 2003; Adam and Kroll, 2012). The main reasons were behavioral deviations from the rational expectation model which often yield empirical results in contradiction to theoretical predictions. Conducting lab experiments have become a standard methodology in this field of research. A challenge in the area of market design is whether with the presence of behavioral biases, market designs still yield efficient outcomes. Our framework is also embedded into this field. With the market mechanism unchanged, what is the impact of adding computer agents on overall market efficiency? The interrelationships of IS constructs, behavioral biases, and market outcome are further discussed in Weinhardt et al. (2003).

Double auctions are a commonly used market mechanism for financial assets, but also for commodities such as at the Chicago Mercantile Exchange. In comparison to other market mechanisms, it provides flexibility for traders to update their trades at any point in time. Moreover, double auctions are efficient and operationally simple. An experimental double auction was first conducted by Smith (1962) who demonstrated the mechanism’s efficiency for different market settings. Based on the seminal work of Smith (1962), further experiments were conducted to demonstrate that a double auction market mechanism can force markets with rational as well as irrational participants to converge to market equilibrium. The latter has been shown by Gode and Sunder (1993) who conducted simulations with zero intelligence (ZI) traders. ZI traders are implemented to post random bids and offers within a specific range and are considered as irrational agents. By imposing a budget constraint on this kind of traders, Gode and Sunder (1993) were able to show that even markets populated with these kinds of traders were able to converge to market equilibrium price. This work has incentivized researchers in computer science to improve agent algorithms with regard to a better performance for a variety of market settings. A prominent type of agent has been developed by Cliff (1997) who named the agents *zero intelligence plus* (ZIP). ZIP is a commonly used agent strategy in the area of agent-based simulation. ZIP traders are able to adapt their profit margin according to previously accepted or rejected bids and offers.

Further work in this field of “agent-human interaction” has been done by Das et al. (2001) and Grossklags and Schmidt (2003). Thereby, this strand of the literature has put an emphasis on the improvement of agent algorithms and it was also restricted to an economically small number of observations. Das et al. (2001) studied fast and slow agents in mixed human-agent markets, but were not able to make robust inferences on the impact of agent speed on market efficiency due to a limited number of observations. Empirical research in finance has shown that latency and speed matters for the market quality and for trading profits (e.g., Riordan and Storkenmaier, 2012; Scholtus and Van Dijk, 2012; Zhang, 2012).

Implications for Market Design and Limitations

In our case study, we focus on the competitive interaction of humans and computer agents in the context of a financial market. Although the experiment is not framed as a financial asset experiment, the design is closely related to a continuous double auction as used at professional stock exchanges such as NYSE and AMEX. In order to simplify the market design and to ensure comprehensibility, we restrict the design to one asset and one market. Additional assets as well as parallel markets would add more complexity to the setting and are an interesting extension for future research. Regarding market outcome, we specifically concentrate on market efficiency in our study since it is an important performance criterion and one of the main regulatory concerns in the current debate on HFT.

Following previous work in the area of NeuroIS, we apply NeuroIS tools in order to analyze human-computer interaction in our proposed competitive financial market setting. In order to gain statistical significant results, the number of participants per session as well as the number of sessions conducted must be sufficiently high. As pointed out by Dimoka et al. (2012), due to the high cost and time constraints, fMRI measurements might not be useful for IS theories at the strategy level. Therefore, we focus on psychophysiological parameters, specifically ECG and SCR, which offer real-time data. Another important reason for focusing on these measures is that markets inherently comprise the strategic interaction of many subjects. In our case study, we simultaneously measure physiological parameters of up to 12 human traders. Rustichini et al. (1994) theoretically analyzed possible inefficiencies resulting from an insufficient number of traders. This inefficiency vanishes as soon as more traders are involved. In more detail, given the expected inefficiency of a double auction as $O(1/m)$, doubling the number of buyer and seller pairs would result in an expected inefficiency of $O(1/m^{1/2})$. With a number of 6 buyers and sellers as in our case, the expected inefficiency approaches to the one of an optimal mechanism with a precision of 0.0001 (cf. Rustichini et al. 1994). Therefore, we concentrate solely on the psychophysiological measures of the NeuroIS toolset. These measures provide data that is retrievable in real-time and from a larger pool of subjects.

In order to ensure a competitive setting, we choose to populate some markets with ZIP agents. For double auctions, ZIP agents, though rather minimalistic, are sufficiently sophisticated to outperform human traders in specific settings (cf. Das et al. 2001). In order to make inferences of the specific impact of computer agents on human participants and test for significant differences in trading behavior and market efficiency, the treatment structure has to involve treatments with and without computer agents. We further introduce treatments for which we analyze whether the speed in which trading agents react plays a significant role for the behavior and emotional state of humans agents and eventually for market efficiency.

The framework might be extended with respect to supportive agents that rather provide liquidity than compete for trading profits. Computer agents as market makers would be an interesting aspect since the questions remains whether a human market maker would improve liquidity and efficiency more than a computer agent acting as a market maker. Furthermore, market design can be more complex than the simple double auction that we propose. Next to additional assets and markets, one might introduce special order types, such as hidden orders (i.e. orders that are invisible in the limit order book). An experiment without computer agents on this market microstructure issue has already been conducted by Bloomfield et al. (2011). The important question here is whether human traders submit more hidden orders in the presence of computer agents. Though these additional features would be possible, complex negotiations between humans and computer agents would be challenging to design and the success would be difficult to measure. At this stage, these aspects are beyond the scope of our research framework. For cooperative situations, it only offers performance criteria on the aggregate level, such as trading profits or market efficiency and liquidity. Finally, a market setting requires a critical number of participants to

provide a sufficient result regarding market efficiency as noted above. We are thus restricted to methods that are applicable to a large number of people. The application of more sophisticated tools, such as fMRI, would be highly desirable, but unrealistic to achieve at the current state of technology.

In conclusion, the framework offers a large variety of possibilities for further extension. The framework is intended to link emotional and behavioral biases with regard to human-computer interaction to market outcomes and support research on HCI in a market setting.

Case Study: The Impact of Competitive Agents on Financial Markets

Based on the market framework of human-computer interaction that we introduced in the last section, we now present a case study that investigates the impact of competitive agents on financial markets. More specifically, we investigate how the presence of competitive agents affects the overall market efficiency as well as the human traders' emotions and decision in a double auction. Thereby, the human traders as well as the trading agents either have the role of a seller or the role of a buyer. Previous studies provided robust empirical and theoretical evidence of a convergence of transaction price to market equilibrium in double auction markets (cf. Smith 1962, Gode and Sunder 1993). The following experimental design has not been thoroughly tested, but applied in several trial sessions to ensure comprehensibility and usability of the software.

Market Design

The market design of our case study builds on the experiment of Gode and Sunder (1993). Each market is constituted by six buyers and six sellers. Each participant of the experiment either takes the role of a buyer or a seller. Gode and Sunder (1993) conducted their experiment for 5 different market settings. The authors defined a market setting as specific supply and demand functions, which simulate characteristic market situations; such as a market in which buyers have a higher market power than sellers (buyer market) and vice versa (seller market). In our experiment, we distinguish between five different market settings. The first three market settings represent realistic market scenarios: a symmetric market, a buyer market, and a seller market. Moreover, for robustness, we introduce two further market settings that reflect abnormal market situations: price convergence and elastic demand (cf. Gode and Sunder, 1993). Each session comprises all three normal and one abnormal market setting.¹ Every market setting is played for 6 consecutive trading periods.

In each trading period, every trader is allowed to trade 6 units of an unspecified commodity. A buyer is privately informed of his or her redemption value v_i for unit i , $i=\{1, \dots, 6\}$, and his trading profits for trading the i^{th} unit is computed as $v_i - p_i$. The information about the (redemption) value of the $(i+1)^{\text{th}}$ is given to the buyer after the successful sell of his i^{th} unit. The (redemption) values for the six units of his or her tradable units per trading period are sorted in descending order. On the other side, a seller is privately informed of his cost v_i for unit i , $i=\{1, \dots, 6\}$, and his trading profits for trading the i^{th} unit is computed as $p_i - v_i$. The information about the redemption value of the $(i+1)^{\text{th}}$ is given to the seller after the successful buy of his i^{th} unit. The costs for the six units of his or her tradable units per trading period are sorted in ascending order. Each limit order and each transaction is valid for a single unit, all orders are cancelled after a transaction, and a crossing of bid and ask prices leads to a transaction equal to the earlier of the two.

Following the induced value theory of Smith (1976), we directly link the actions of the participants to real monetary payoffs and plan to conduct the experiment with university students with an economics-related background. Students have been frequently used as probands in order to investigate human behavior in economic experiments (Kagel and Roth, 1995). Students have a steep learning curve and can be easily incentivized with a proper reward scheme. For example, the observations in the seminal paper by Smith (1962) are based on classroom experiments. The design of a simplified double-auction offers sufficient simplicity to be understood by university students. Additionally, we ask 8 comprehension questions beforehand in order to ensure comprehension of the market design. Furthermore, we also plan to conduct

¹ The order of the market settings is randomized in order to control for learning effects and exhaustion.

sessions with professional traders in order to check the robustness of our results. Depending on their trading behavior in the experiment, the average payoff is approximately €25.00 per participant.

Treatment Structure

The experiment comprises six treatments which are summarized in Table 1. In the human vs. human (HH) treatment, there are six human buyers trading with six human sellers. In current financial markets, the number of algorithmic trading agents is constantly increasing, but the information about the counterparts of a specific trade is often unknown. We account for this fact by introducing treatments in which half of the traders is represented by computer agents. Thus, in the 6HSA and the 6HFA treatment, the market is populated with three human traders and three computer agents who are buyers, and three human traders and three computer agents who are sellers. Moreover, we introduce two treatments in which one single human trader interacts with eleven computer agents (1HSA and 1HFA). Thereby, we can control for clean analysis of the effect between interacting with other human traders. The agents vs. agents (AA) treatment only comprises computer agents.

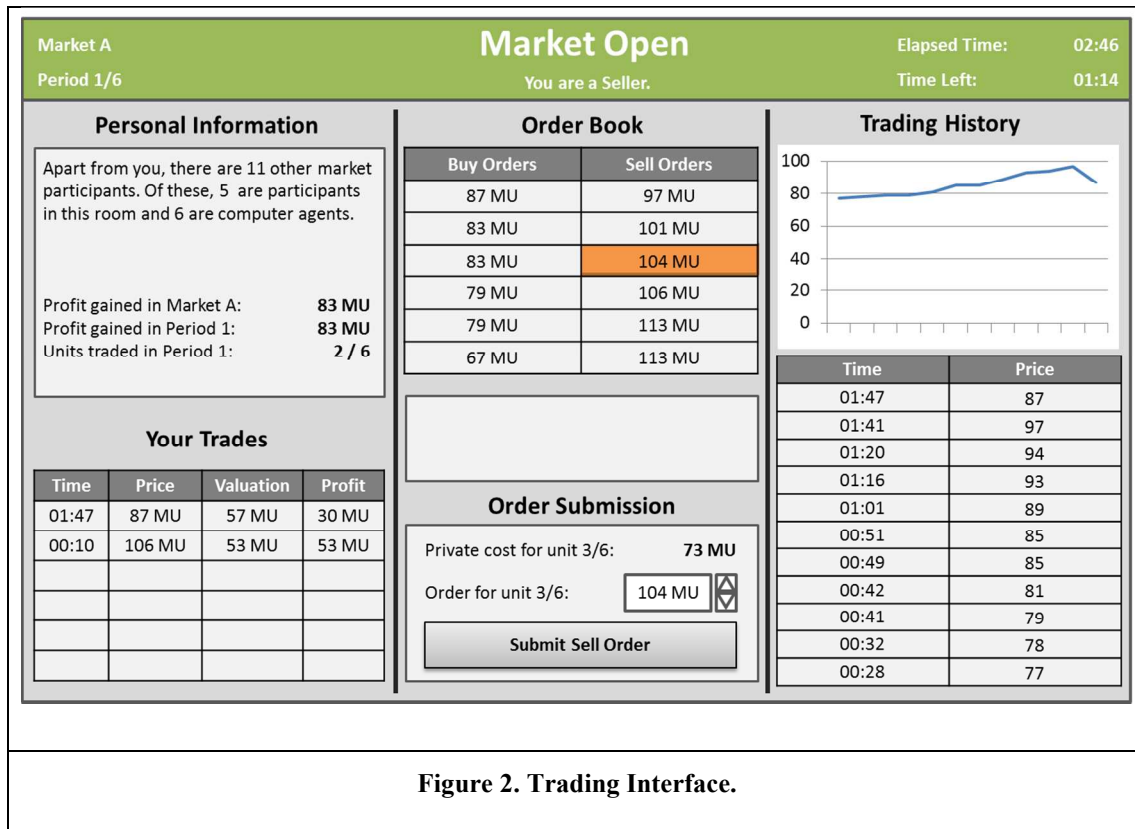
Treatment	Number of Human Traders	Number of Trading Agents
HH	12	0
6HSA	6	6 (Slow)
6HFA		6 (Fast)
1HSA	1	11 (Slow)
1HFA		11 (Fast)
AA	0	12

We further distinguish between fast agents that have a sleep/wake cycle of 0.5 seconds +/- 50% (6HFA, 1HFA) and slow agents which have a sleep/wake cycle of 5 seconds +/- 50% (6HSA, 1HSA). This means that the agents are only allowed to submit or update their orders after a specific interval and stay inactive or “asleep” otherwise. The experiment is based on a between-subjects design, i.e. the subjects exclusively participate in one of the 6 treatments and they keep their role as a buyer or a seller for the whole session. In order to allow for physiological parameters to be measured, the experiment follows the physioeconomic session framework of Adam et al. (2011a). Thus, we introduce specific waiting times and an initial five minute rest period which is necessary for calibrating the physiological measurement for the individual participants. Another important aspect is that the participants of the experiment are equipped with earmuffs to avoid susceptibility to background noise. Finally, we keep environmental conditions as constant as possible and in the range of the recommended thresholds.

Implementation

The market platform is based on the OpenExchange software environment. OpenExchange is an open-source trading software developed by De Luca and Cliff (2011a) and applied in De Luca and Cliff (2011b). We change the market design according to the description above.

The trading interface is depicted in Figure 2. The trading interface includes the most essential information necessary for trading. The left hand side contains the personal information for a specific trader, such as the treatment he or she is in, the profit gained, the units traded, and the trade he or she made. The middle part of the interface provides information for the order submission. At the top is the order book in which the traders can see all the orders submitted by other traders as well as his own order ordered by price and then by the time of submission. The order submission panel offers information about the value or cost of the current unit of commodity that is currently traded. The right hand side contains the trade history of the whole market.



Conclusion and Further Research Agenda

We contribute to current NeuroIS research by adding a focus to the competitive interaction of human traders and computer agents. In particular, we introduce a framework for the analysis of human-computer interaction in a financial market setting using NeuroIS tools. Our market framework for human-computer interaction combines NeuroIS methods and research areas close to the fields of NeuroIS and human-computer interaction. The framework provides a guideline for further studies of real world phenomena including both human actors as well as computer agents.

The experiment design that we present in our case study is based on previous studies of large-scale double auctions. We further apply psychophysiological methods of the NeuroIS toolset in order to gain a sufficiently high amount of observations to make economic statements. The application of different agent speeds allows us to make further inferences on current discussions about high-frequency trading. A possible impact would be that a growing sophistication and speed of agents might lead human traders to trade more aggressively and take more risks in order to make a trade. Depending on the reaction of human traders, we hypothesize that this also leads to significant differences in market efficiency.

There are possible extensions for the framework for human-computer interaction. The framework is not restricted to competitive computer agents, but can also be applied to the group of supportive computer agents as discussed in the section “Methodological Framework and Related Work” in the context of implications for market design. Transfers to industries other than the financial market setting applied in our study are also possible. Examples are recent work on agent-mediation in automated negotiations, often applied in e-commerce, as described by Guttman et al. (1998) and He (2003). These extensions are beyond the scope of our paper but may be interesting for future research. We believe that the framework offers various possibilities for the analysis of related research questions in the field of competitive human agent interaction and we hope to stimulate further research in this field.

References

- Adam, M. T. P., Gamer, M., Krämer, J., and Weinhardt, C. 2011a. "Measuring Emotions in Electronic Markets," in *Proceedings of the 32nd International Conference on Information Systems*, Shanghai, China.
- Adam, M. T. P., Krämer, J., Jähmig, C., Seifert, S., and Weinhardt, C. 2011b. "Understanding Auction Fever: A Framework for Emotional Bidding," *Electronic Markets* (21:3), pp.197-207.
- Adam, M. T. P., Krämer, J., and Weinhardt, C. forthcoming. "Excitement up! Price down! Measuring emotions in Dutch auctions," *International Journal of Electronic Commerce*.
- Adam, M. T. P., and Kroll, E. 2012. "Physiological evidence of attraction to chance," *Journal of Neuroscience, Psychology, and Economics* (5:3), pp. 152–165.
- Al-Natour, S., Benbasat, I., and Cenfetelli, R. T. 2006. "The Role of Design Characteristics in Shaping Perceptions of Similarity: The Case of Online Shopping Assistants," *Journal of the Association for Information Systems* (7:12), pp. 821–861.
- Ariely, D., Ockenfels, A., and Roth, A. E. 2005. "An experimental analysis of ending rules in Internet auctions," *The RAND Journal of Economics* (36:4), pp. 890–907.
- Benbasat, I., Dimoka, A., Pavlou, P. A., and Qiu, L. 2010. "Incorporating Social Presence in the Design of the Anthropomorphic Interface of Recommendation Agents: Insights from an fMRI Study," in *Proceedings of the 31st International Conference on Information Systems*, St. Louis, Missouri, USA.
- Bloomfield, R., O'Hara, M., and Saar, G. 2011. "Hidden Liquidity: Some new light on dark trading," *Working Paper*.
- Camerer, C. F. 2003. "Behavioral game theory: Experiments in strategic interaction," Princeton, NJ: Princeton University Press.
- Das, R., Hanson, J., Kephart, J., and Tesauro, G. 2001. "Agent-human Interactions in the Continuous Double Auction," in *Proceedings of the IJCAI-01*.
- De Luca, M., Szostek, C., Carlidge, J., and Cliff, D. 2011. "Studies on interactions between human traders and Algorithmic Trading Systems," *The Future of Computer Trading in Financial Markets – Foresight Driver Review DR 13*.
- De Luca, M. and Cliff, D. 2011a. "Agent-Human Interactions in the Continuous Double Auction, Redux: Using the OpEx Lab-in-a-Box to explore ZIP and GDX," in *Proceedings of the 3rd International Conference on Agents and Artificial Intelligence (ICAART-2011)*, Rome, Italy.
- De Luca, M. and Cliff, D. 2011b. "Human-Agent Auction Interactions: Adaptive-Aggressive Agents Dominate," In *Proceedings of the 22nd International Joint Conference on Artificial Intelligence (IJCAI-2011)*.
- Decety, J., Jackson, P. L., Sommerville, J. A., Chaminade, T., and Meltzoff, A. N. 2004. "The Neural Bases of Cooperation and Competition: An fMRI investigation," *NeuroImage* (23:2). pp. 744-751.
- Dimoka, A., Pavlou, P. A., Davis, F. D. 2007 "Neuro-IS: The Potential of Cognitive Neuroscience for Information Systems Research," in *Proceedings of the 27th International Conference on Information Systems*, Montreal, Canada.
- Dimoka, A., and Davis, F. D. 2008. "Where Does TAM Reside in the Brain? The Neural Mechanisms Underlying Technology Adoption," in *Proceedings of the 28th International Conference on Information Systems*, Paris, France.
- Dimoka, A. 2010. "What Does the Brain Tell Us about Trust and Distrust? Evidence from a Functional Neuroimaging Study," *MIS Quarterly* (34:2), pp. 373–396.
- Dimoka, A., Pavlou, P. A., and Davis, F. D. 2011. "NeuroIS: The Potential of Cognitive Neuroscience for Information Systems Research," *Information Systems Research* (22:4), pp. 687–702.
- Dimoka, A., Banker, R. D., Benbasat, I., Davis, F. D., Dennis, A. R., Gefen, D., Gupta, A., Ischebeck, A., Kenning, P., Müller-Putz, G., Pavlou, P. A., Riedl, R., vom Brocke, J., and Weber, B. 2012. "On the Use of Neurophysiological Tools in IS Research: Developing a Research Agenda for NeuroIS," *MIS Quarterly* (36:3), pp. 679–702.
- Gallagher, H. L., Jack, A. I., Roepstorff, A., and Frith, C. D. 2002. "Imaging the Intentional Stance in a Competitive Game," *NeuroImage* (16:3), pp. 814–821.
- Gode, D. K., and Sunder, S. 1993. "Allocative Efficiency of Markets with Zero-Intelligence Traders: Market as a Partial Substitute for Individual Rationality," *Journal of Political Economy* (101:1), pp. 119–137.

- Grossklags, J., and Schmidt, C. 2003. "Artificial Software Agents on Thin Double Auction Markets: A Human Trader Experiment," in *Proceedings of the IEEE/WIC International Conference on Intelligent Agent Technology (IAT)*, pp. 400–407.
- Grossklags, J., and Schmidt, C. 2006. "Software Agents and Market (In) Efficiency: A Human Trader Experiment," In *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)* (36:1), pp. 56–67.
- Güth, W., Schmittberger, R., and Schwarze, B. 1982. "An Experimental Analysis of Ultimatum Bargaining," *Journal of Economic Behavior and Organization* (3:4), pp. 367–388.
- Guttman, R. H., Moukas, A. G., and Maes, P. 1998. "Agent-mediated Electronic Commerce: A Survey," *The Knowledge Engineering Review* (13:2), pp. 147–159.
- He, M., Jennings, N. R., Jennings, and Leung H. 2003. "On agent-mediated electronic commerce," *IEEE Transactions on Knowledge and Data Engineering* (15), pp. 985–1003.
- Kagel, J. H., and Roth, A. E. 1995. *The handbook of experimental economics*, Princeton, NJ: Princeton University Press.
- Ku, G., Malhotra, D., and Murnighan, J. K. 2005. "Towards a competitive arousal model of decision-making: A study of auction fever in live and Internet auction," *Organizational Behavior and Human Decision Processes* (96:2), pp. 89–103.
- Muth, J. F. 1961 "Rational Expectations and the Theory of Price Movements," *Econometrica* (29:3), pp. 315–335
- Riedl, R., Hubert, M., and Kenning, P. 2010a. "Are There Neural Gender Differences in Online Trust? An fMRI Study on the Perceived Trustworthiness of eBay Offers," *MIS Quarterly* (34:2), pp. 397–428.
- Riedl, R., Banker, R. D., Benbasat, I., Davis, F. D., Dennis, A. R., Dimoka, A., Gefen, D., Gupta, A., Ischebeck, A., Kenning, P., Müller-Putz, G., Pavlou, P. A., Straub, D. W., vom Brocke, J., Weber, B. 2010b. "On the Foundations of NeuroIS: Reflections on the Gmunden Retreat 2009," *Communications of the Association for Information Systems* (27), pp. 243–264.
- Riedl, R., Mohr, P., Kenning, P., Davis, F. D., and Heekeren, H. 2011. "Trusting Humans and Avatars: Behavioral and Neural Evidence," in *Proceedings of the 32nd International Conference on Information Systems*, Shanghai, China.
- Riedl, R., Kindermann, H., Auinger, A., and Javor, A. 2012. "Technostress from a Neurobiological Perspective: System Breakdown increases the Stress Hormone Cortisol in Computer Users," *Business & Information Systems Engineering* (4:2), pp. 61–69.
- Riordan, R., and Storkenmaier, A. 2012. "Latency, Liquidity, and Price Discovery," *Journal of Financial Markets*, forthcoming.
- Rustichini, A., Satterthwaite, M. A., and Williams, S. R. 1994. "Convergence to Efficiency in a Simple Market with Incomplete Information," *Econometrica* (62:5), pp. 1041–1063.
- Sanfey, A. G., Rilling, J. K., Aronson, J. A., Nystrom, L. E., and Cohen, J. D. 2003. "The Neural Basis of Economic Decision-Making in the Ultimatum Game," *Science* (300:5626), pp. 1755–1758.
- Scholtus, M. L. and Van Dijk, D. J. C. 2012. "High-Frequency Technical Trading: The Importance of Speed," Working Paper.
- Smith, A. 1776. "An Inquiry into the Nature and Causes of the Wealth of Nations," *Edwin Cannan, ed. 1904*, Library of Economics and Liberty.
- Smith, V. L. 1962. "An Experimental Study of Competitive Market Behavior," *The Journal of Political Economy* (70:2), pp. 111–137.
- Smith, V. L. 1976. "Experimental economics: Induced value theory," *The American Economic Review* (66:2), pp. 274–279.
- Tabb, L., Iati, R., and Sussman, A. 2009. "US equity high frequency trading: Strategies, sizing, and market structure," TABB Group report.
- Wang, W., and Benbasat, I. 2005. "Trust in and Adoption of Online Recommendation Agents," *Journal of the Association for Information Systems* (6:3), pp. 72–101.
- Weinhardt, C., Holtmann, C., and Neumann, D. 2003. "Market Engineering," *Wirtschaftsinformatik* (45:6), pp.635–640.
- Williams, R. B. and Clippinger, C. A. 2002. "Aggression, competition and computer games: computer and human opponents," *Computers in Human Behavior* (18:5), pp. 495–506.
- Zhang, S. S., Wagener, M., Storkenmaier, A., and Weinhardt, C. 2011. "The Quality of Electronic Markets," in *Proceedings of the 44th Hawaii International Conference on System Sciences*, Koloa, USA.
- Zhang, S. S. 2012. "Need for Speed: An Empirical Analysis of Hard and Soft Information in a High Frequency World," Working Paper.