High Frequency Trading in Financial Markets

Zur Erlangung des akademischen Grades eines
Doktors der Wirtschaftswissenschaften

(Dr. rer. pol.)

von der Fakultät für
Wirtschaftswissenschaften
am Karlsruher Institut für Technologie (KIT)

genehmigte

DISSERTATION

von

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Tag der mündlichen Prüfung: 11.12.2013
Referent: Prof. Dr. Christof Weinhardt
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2013 Karlsruhe

Acknowledgements

I would like to express my deep gratitude to Prof. Dr. Christof Weinhardt for giving me the opportunity to pursue my research interests at the Institute of Information Systems and Marketing (IISM) and for his support and advice throughout my dissertation. I would further like to thank Prof. Dr. Ryan Riordan for his guidance and without whom this work would not have been possible.

I would also like to thank Prof. Dr. Marliese Uhrig-Homburg for insightful discussions and helpful comments. My thanks also go to Prof. Dr. Martin Ruckes and Prof. Dr. Kay Mitusch for serving on my thesis committee. I am also very grateful to Prof. Albert S. Kyle, Prof. Andreas Park, and Prof. Peter Cziraki for comments on my work and for their support - it made all the difference.

My sincere thanks go to my colleagues at the IISM. I could not have wished for better collegues. In particular I would like to thank my colleagues Dr. Marc Adam, Stephan Meyer, Dr. Andreas Storkenmaier, Dr. Florian Teschner, and Dr. Martin Wagener for their feedback and guidance. It has been a privilege to be a member of this inspiring and enthusiastic team.

I gratefully acknowledge financial support by the IME Graduate School at the Karlsruhe Institute of Technology (KIT) funded by Deutsche Forschungsgemeinschaft (DFG) and financial support by the Karlsruhe House of Young Scientists (KHYS) for the research stay at University of Toronto.

Finally, but most importantly, I thank my family and friends. I thank my parents Lanju and Wucheng for their unconditional love and support throughout my life, and Dominik for his love, forbearance, and encouragement. I owe them more than I can ever put in words.

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List of Abbreviations

AFME	Association for Financial Markets in Europe
AT	Algorithmic Trading
ATs	Algorithmic Traders
ATS	Alternative Trading System
CBOE	Chicago Board Options Exchange
CEP	Complex Event Processing
CFTC	U.S. Commodity Futures Trading Commission
CME	Chicago Mercantile Exchange
DAX	Deutscher Aktien Index
DMA	Direct Market Access
DWZ	Deutsche Wertpapier-Datezentrale
EBS	Electronic Broking Services
ECG	Electrocardiography
ECN	Electronic Communication Networks
EEG	Electroencephalography
EMG	Facial Electromyography
ER	Emotion Regulation
ETF	Exchange-Traded Fund
Eurex	European Exchange
FCA	Financial Conduct Authority
fMRI	functional Magnetic Resonance Imaging
HCI	Human-Computer Interaction
HFT	High Frequency Trading
HFTs	High Frequency Traders
HR	Heart Rate
IBIS I	Inter-Banken-Informations-System
IBIS II	Integriertes Boersenhandels- und Informationssystem
ICAP	Intercapital
IS	Implementation Shortfall
LSE	London Stock Exchange
MAD	Market Abuse Directive
MiFID	Markets in Financial Instruments Directive
MTF	Multilateral Trading Facilities
Nasdaq	National Association of Securities Dealers and Automated Quotations

non-HFT	non-High Frequency Trading
non-HFTs	non-High Frequency Traders
NYSE	New York Stock Exchange
RegNMQ	Regulation National Market System
RNSE	Reuters NewsScope Sentiment Engine
SA	Sponsored Access
SCR	Skin Conductance Response
SEC	Securities and Exchange Commission
SIRCA	Securities Industry Research Centre of Asia-Pacific
S&P 500	Standard & Poor's 500
TWAP	Time-Weighted Average Price
VaR	Value-at-Risk
VAR	Vector Autoregression
VMA	Vector Moving Average
VWAP	Volume-Weighted Average Price
WFE	World Federation of Exchanges
Xetra	Exchange Electronic Trading
ZI	Zero Intelligence
ZIP	Zero Intelligence Plus

Chapter 1

Motivation and Introduction

Technological innovation has always been a driving factor in the development of financial markets. Starting with the computerization of tasks on trading floors, through the introduction of completely electronic markets, to Algorithmic Trading (AT) and High Frequency Trading (HFT), trading has become almost completely automated. Prerequisites for this electronic evolution of financial markets are the technological advances made in the area of information and communication technology. Over the last decade, this has also made the increasing use of AT and HFT systems[1] possible, which has had immense technological and economic impact on investors and marketplaces. In 2012, HFT made up more than 50% of U.S. equity trading volume and more than 30% of equity trading volume in Europe (cf. Sussman, 2012). Despite its importance, the role of HFT in financial markets is still not well understood.

An incident on May 6, 2010, the so-called "Flash Crash", has drawn the attention of the regulatory authorities and the public to HFT. The "Flash Crash" was a crash in the U.S. stock market which resulted in a rapid drop in major U.S. indices and a similarly rapid recovery within half an hour. With this incident, the current market structure has revealed serious vulnerabilities that may be exacerbated by HFT. Kirilenko et al. (2011) find that HFT did not cause the "Flash Crash", but that it exacerbated market

[1] AT is defined as "the use of computer algorithms to automatically make trading decisions, submit orders, and manage those orders after submission" (Hendershott et al., 2011). HFT is considered as a subcategory of AT and includes more sophisticated and complex strategies that make use of the fast connection and processing speed of computers. See Chapter 2 for a more detailed discussion of HFT definitions.

volatility during the crash. Thus, it is crucial to gain knowledge of HFT behavior during normal and extreme market conditions in order to make regulatory decisions in the best interest of financial markets in general and of different groups of traders. The World Federation of Exchanges (WFE) points out that “[a]lthough there have always been occasional trading errors and episodic volatility spikes in markets, the speed, automation and interconnectedness of today’s markets create a different scale of risk” (World Federation of Exchanges, 2013).

Since the trading process is central to efficient risk sharing and price efficiency, it is important for regulators, market operators, and investors to understand the role of HFT in this interconnected high frequency world and the implications for financial market design and trading behavior. In this context, there are also different perspectives of the view on HFT. Market quality and how HFT contributes to the different dimensions of market quality is a major concern for all interest groups. While higher market efficiency and liquidity is desirable for markets in general, the protection of investors is yet another goal of regulatory authorities, such as the U.S. Securities and Exchange Commission (SEC). Therefore, another issue next to market quality is whether HFT puts individual investors at a disadvantage and leads to differences in their trading behavior and strategies.

1.1 Modern Financial Markets

In today’s modern financial markets, market operators have to cope with a multiple of the trading volume and message traffic than around a decade ago. Angel et al. (2011) show that daily U.S. equity share volume increased more than threefold, “from about 3 billion shares per day in 2003 to nearly 10 billion shares per day in 2009” (p. 5, Angel et al., 2011), that quote frequency dramatically increased from below 50 quotes per minute to up to more than 500 (cf. Figure 16, Angel et al., 2011), and that execution speed fell significantly as well. In light of this development, trading venues increased IT investments and adopted more innovative technologies in order to handle increased activity and attract order flow and thus profit. Due to their high trading volume, HFT has become an especially important source of profit for trading venues.

1.1.1 Technological Innovation in Financial Markets

Infrastructure investments by market operators mainly concern latency and risk management aspects as well as platform stability and reliability. In terms of latency reductions, co-location services offered by marketplaces have become common, i.e. "enable exchange customers to place their servers in close proximity to the exchange's matching engine" SEC (2010) in order to further reduce latency. In 2009, NYSE Euronext built a 400,000 sq. foot data center in New Jersey, while CME opened a 428,000 sq. foot data center in 2012 in order to serve the colocation demand of clients (Wall Street and Technology, 2011). However, the SEC raised the questions (see Section IV.B.2. in their call for comments on the US equity market structure in 2010 SEC, 2010) about the fairness of co-location to long-term investors, whether it improved market quality, and whether the use of co-location should involve trading obligations to counterbalance the speed advantage.

Immense IT investments have further been made in order to reduce the latency between different marketplaces, e.g. using fiber-optic cables. The cost of a fiber connection between Chicago and New York is estimated to around $200,000 per mile, resulting in round trip latencies below 9 milliseconds (Forbes, 2010). The construction of a high-speed cable connection between London and New York totals to around $300 million, reducing latency from 64 milliseconds per round-trip to 59.6 milliseconds and making it the world's fastest transatlantic cable in 2013 (Bloomberg Business Week, 2012). These services are specifically catered to HFT, considering that the reaction time of the human brain is around 110-120 milliseconds and the blink of an eye takes 200 milliseconds (Timms, 2012).

New trends in the area of latency reduction are microwave and laser technologies. For the route from London to Frankfurt, Perseus, a network operator specialized in building ultra-low latency networks, says its microwave system has decreased the roundtrip time from 8.35 milliseconds for its fiber-optic network to below 4.6 milliseconds (Reuters, 2013b). Another leap in this sector will be provided by competitor ANOVA Technologies with its new hybrid system of lasers and millimeter waves wireless dishes. CEO Michael Persico states that this technology will be “on par with fiber-optic cable in terms of availability - and continue to surpass it in terms of speed, [... increasing] the current availability of wireless networks from 95% to 99.99%” (p.46, Hammer, 2013). These technological advances will bring transmission speed even closer to the speed of light.

With latency reduction reaching this natural threshold, HFT firms are developing more complex strategies in order to gain another competitive edge towards their competitors. One of the current trends include trading on machine-readable news, which have made computerized trading on complex information easier (New York Times, 2010). Recent investments have been made by NASDAQ and Deutsche Börse to integrate machine-readable economic news into their line of services offered for trading firms and specifically automated traders (Wall Street Journal, 2011b). Current research in computer science, e.g. in the area of sentiment analysis, is further evolving to use social media, such as Twitter messages, to predict box-office revenues for movies (Asur, 2010) and market returns (Bollen et al., 2011). When asked about the next “quantum leap” in technology, executives of Bottom Line Metrics, a technology solutions provider, suggested Complex Event Processing (CEP) which will further help to manage risk in real-time in this high-speed environment (p.150, Hammer, 2013). Used for alpha-seeking strategies as well as for the execution of trading decisions, it serves as an additional tool for AT and HFT systems in order to make exact decisions based on the analysis of large volumes of fast-moving data (c.f. Waters Technology, 2013).

1.1.2 The Role of HFT

Due to the sophistication and the advances made in computing power and network systems, technological innovations, such as HFT, have gained increasing economic importance. In this context, concerns have been raised towards the impact of HFT on market quality and possible systemic risks that it poses to financial markets. The public opinion of practitioners and regulatory authorities on this topic is dominated by scepticism and aversion. In their call for comments in 2010 (SEC, 2010), the SEC addresses different issues regarding the U.S. market structure and specifically raises concerns towards HFT, such as its impact on market quality and certain types of manipulative HFT strategies.

Recent market disturbances have further increased this scepticism, such as the computer glitch on August 1, 2012 by Knight Capital, a large HFT market making company. It was due to not properly tested software and resulted in a loss of $440 million for Knight. In 2013, Knight Capital was acquired by Getco, a leading HFT market-making firm (Bloomberg Businessweek, 2013). In 2013, U.S. Commodity Futures Trading Commission (CFTC), the UK Financial Conduct Authority (FCA), and market operator CME fined an individual, Michael Coscia, over $4 million for conducting HFT market manipulation in commodities markets. This was the first CFTC enforcement action under Dodd-Frank Act that targets discruptive trading practices (Bloomberg, 2013).

While these incidents have put HFT under even higher regulatory scrutiny, most empirical research so far show that HFT activity improves overall liquidity and efficiency (e.g. Hendershott et al., 2011; Jovanovic and Menkveld, 2012; Brogaard et al., 2013), for example by implementing market making or index arbitrage strategies. As stated by Mary Schapiro, the chairman of the SEC, "[r]eliance on computers is a fact of life not only in markets everywhere, but in virtually every facet of business. [...] It'll take a few more Knight Capitals to really create the pressure needed to blow against the wind" (Forbes, 2012). However, specific market manipulation strategies still concern regulators and the role of HFT during extreme market events is also an open question.

In summary, there is no consistently positive or negative image for HFT overall, but there are up and downsides as to every technological innovation. Put by U.S. economist Robert Shiller, "[millisecond trading is] neither really amazingly good nor amazingly bad. It's just an implication of information technology" (Forbes, 2012).

1.1.3 Applications of Financial Market Engineering

Challenges of technological nature, specifically posed by HFT, in modern electronic markets, call for a conscious and revised thinking about financial market structure design, in the context of newly introduced markets, but also of the regulation of existing markets. This area of research falls into the research framework of *Financial Market Engineering*. Financial Market Engineering is defined as

> "[...] an engineering approach to market structure that is needed to help market operators exploit the opportunities for IT-enabled markets while minimizing the risk of failure" (Weinhardt et al., 2006).

Especially in the light of current examples of market failure, a structured way of rethinking some market design choices seems necessary, for market operators as well as for regulators, in order to prevent further market failures from happening. For example in the aftermath of the Flash Crash and with regard to the strong interlinkage of financial markets, the introduction of multi-market volatility breakers have been discussed which halts trading when volatility exceeds a certain threshold. This market design element was implemented in order to prevent that crashes happen and transmit to other markets.

In this thesis, two extensions of the financial market engineering framework are proposed. The *Market Quality Framework* in Chapter 2 provides a structured approach to analyze market quality in modern financial electronic markets in the context of a dynamic competitive, regulatory, and technological environment. The *Market Framework for Human-Computer Interaction* in Chapter 4 extends the market engineering framework by behavioral and psychophysiological aspects of competitive interaction between human traders and computer agents.

1.2 Research Questions and Structure

The goal of this thesis is to shed light into the influence of a specific technological innovation, namely HFT, in the context of the electronic evolution of financial markets. The main part of the thesis is structured into three chapters. Chapter 2 presents aspects of the electronic evolution of financial markets and the role of HFT in this development. Chapter 3 focuses on the role of HFT in the processing of hard and soft information. Chapter 4 researches into effects of fast and slow computer agents on human trading behavior.

Section 2.1 in Chapter 2 provides a conceptual framework to analyze market quality and a discussion of the electronic evolution in financial markets. Section 2.1 is based on the joint paper "The Quality of Electronic Markets" with Martin Wagener, Andreas Storkenmaier, and Christof Weinhardt, which has been presented at the "Hawaii International Conference on System Sciences 2011" (Zhang et al., 2011). The trading landscape has tremendously changed over the last two decades, with respect to market quality, but also to external factors, such as technology and regulation, and internal market structure, such as business and market microstructure. Since the term market quality is often referred to in an ambiguous way, a framework is proposed that puts several prominent measures of market quality into context with external factors and the internal market structure. The framework is applied to a comparative case study, "IBIS vs. Xetra." The case study demonstrates the evolution of financial markets by the example of the German financial market. Specifically, it compares market quality measures as well as the regulatory and technological environment of the two dominant electronic markets in Germany, IBIS II and Xetra. Section 2.1 thus focuses on Research Question 1:

> **Research Question 1:** *How did market quality and external and internal factors of the trading landscape change over the last two decades?*

Based on the proposed framework for market quality and the discussion of regulatory and technological changes, Section 2.2 discusses the role of HFT in financial markets along the factors in the framework. Section 2.2 is based on the joint paper "Technology and Market Quality: The Case of High Frequency Trading" with Ryan Riordan, which has been presented at the "European Conference of Information Systems 2011" (Zhang and Riordan, 2011). The case study on "HFT and Liquidity" shows the improvements of market quality in the context of HFT activity and contribution to liquidity. It specifically focuses on Research Question 2:

> **Research Question 2:** *Which role does HFT play in modern financial markets and for market quality?*

Based on the foundations on the electronic evolution of financial markets in Chapter 2, Chapter 3 specifically analyzes the roles that HFT and non-HFT play in price discovery. Chapter 3 is based on the working paper "Need for Speed: An Empirical Analysis of Hard and Soft Information in a High Frequency World" (Zhang, 2013). Common information processing strategies applied by High Frequency Traders (HFTs) are arbitrage and news trading strategies. Statistical arbitrage realizes profits from mispricings between different assets. Index arbitrage, being a subset of statistical arbitrage, focuses on mispricings between an index (such as the S&P 500 index) and its components. In the context of qualitative textual information, advances have been made to quantify textual information in order to incorporate them into trading strategies. In Chapter 3, I specifically analyze the use of "hard" futures price information for index arbitrage strategies and the use of "soft" textual news information for news trading strategies by HFTs and non-HFTs and implications for price discovery and trading profits. Chapter 3 thus focuses on Research Questions 3a-3c:

> **Research Question 3a:** *What is the market impact of hard and soft information events?*
>
> **Research Question 3b:** *How do HFT and NHFT process hard and soft information shocks?*
>
> **Research Question 3c:** *What is the value of speed in information processing?*

While HFT plays an important role for market liquidity and price discovery, regulators are also concerned about the influences on individual human investors. These are prone to behavioral biases and disadvantaged with respect to speed and processing capabilities when competing with computerized agents. Chapter 4 presents the design and results of an economic laboratory experiment which sheds light into the direct effects of the presence of fast and slow computer agents on human arousal and trading behavior and how this translates into differences in market efficiency. Chapter 4 is based on a paper which has been presented as a joint research-in-progress paper "Humans versus Agents: Competition in Financial Markets of the 21st century" with Marc Adam and Christof Weinhardt, which has been presented at the "International Conference on Information Systems 2012" (Zhang et al., 2012). These objectives are reflected in Research Questions 4a-4b:

Research Question 4a: *Are humans more or less emotionally aroused when trading against computer agents than against other humans?*

Research Question 4b: *Do differences in emotional arousal affect trading behavior?*

Research Question 4c: *Do differences in human trading behavior in turn translate into differences in market quality?*

Finally, Chapter 5 summarizes the findings of this thesis and discusses implications for regulators and policy makers, market operators, and investors. Furthermore, it outlines the interface with other areas in finance and information systems research and provides a guideline for future research.

Chapter 2

HFT and the Electronic Evolution of Financial Markets

This chapter discusses technological innovation in the context of the electronic evolution of financial markets over the last decades, with a focus on HFT, and its impact on market quality. Technological innovation had a profound impact on financial markets and serves as support of the trading process and trading decisions. As put by Frame and White (2004), "the basic underlying "physical" technologies of finance are those of telecommunications and data processing, which permit the gathering of information, its transmission, and its analysis. [B]etter (more advanced, faster, lower-cost) physical technologies have permitted more innovations (e.g., credit and behavioral scoring) that allow lenders better to overcome those asymmetric information problems. [...] Better physical technologies may also permit organizational innovations (e.g., electronic securities exchanges) that would not be possible with less advanced technologies." Since the postulate of Frame and White (2004), an increasing amount of research has been conducted in the field of financial innovation.

Section 2.1 provides an overview of this literature with a focus on technological innovation. It further discusses existing measures of market quality and relates them to a methodological framework of market quality (cf. Zhang et al., 2011). The changes in market quality over time are further demonstrated in a comparative case study of the two prevailing electronic systems in Germany of their time, IBIS II and Xetra. Section 2.2 analyzes and discusses the role of HFT as a technological innovation in this dynamic environment and its contribution to market quality. Section 2.3 summarizes findings in this chapter.

2.1 The Electronic Evolution of Financial Markets

Innovations in information and communication technology have profoundly changed the design and operation of financial markets over the last decades, making trading without the use of IT systems impossible. While the introduction of electronic trading can be considered a revolution in securities trading, a lot of change that happened since then has been gradual and incremental. In this context, Jürgen Spillmann, the deputy CEO and head of IT and operations for Eurex Exchange and Eurex Clearing, states: “You cannot have revolutionary changes every year and expect the market to keep up. Our goal is a continuum” (Hammer, 2013).

While market quality has simultaneously improved (Chordia et al., 2011; Angel et al., 2011), much of its improvement is attributed to technological innovations, such as AT (Hendershott et al., 2011), automation, and IT system updates (e.g. Jain, 2005; Hendershott and Moulton, 2011; Riordan and Storkenmaier, 2012). Factors other than technological innovation, such as the rapidly changing regulatory environment and the adjusting internal market structures, also have to be taken into account in the discussion of improving market quality.

2.1.1 Measures of Market Quality

Academics and practitioners refer to the term market quality in a very ambiguous way, often in terms of liquidity measures, specifically spreads and trading intensity, or information and efficiency measures, for instance price impacts and price reversals. Since market quality can involve different aspects, a framework is proposed that highlights common measures in finance literature, namely market activity, liquidity, and price efficiency, and puts these measures of market quality into context with external factors and internal market structure.

Activity, Volume, and Trade Sizes

Activity can be measured using measures like the traded dollar volume (Turnover), the number of trades (Transactions), or the average trade size (Trade Size) (e.g. Chordia et al., 2011; Barclay et al., 2003; Bessembinder, 1999), usually on a daily basis per instrument. These measures are closely related. An increase in transactions does not unconditionally imply an increase in turnover, since trade sizes also have to be taken into account. Chordia et al. (2011) show that turnover and number of transactions per day have been increasing from 1993 to 2008 at an accelerating rate, while average trade size has simultaneously declined from up to $ 90,000 in the mid 1990's to around $ 7,000 in 2008. They further find that this trend has been influenced by decreases in trading costs and that institutional trading has been a key contributor for this development.

While all three measures can be classified as trading intensity, quote updates can be considered as a measure for the mere market activity of traders. Especially in the context of increasing HFT activity, this has become an important issue for trading venues. Message traffic in terms of order submissions and cancellations have increased disproportionately to the increase in transactions. This poses an excessive overload of technological processing capacity which requires higher investments of trading venues into their IT systems. Without any market quality improvements due to these investments, this poses a negative externality to marketplaces. Gai et al. (2012) analyze the installation of a new matching machine at NASDAQ in May 2010. The installation led to the entering of a nanosecond regime in trading and to increases in cancellation to execution ratio without any market quality improvement. They argue that HFTs submit and cancel orders excessively in order to generate congestion and slow down other traders which falls into the group of manipulative strategies.

Liquidity

Liquidity indicates "the ability to trade large size quickly, at low cost, when you want to trade" (cf. p.394, Harris, 2003). It also affects external factors, i.e. regulation as well as competition: "Everyone likes liquidity. Traders like liquidity because it allows them to implement their trading strategies cheaply. Exchanges like liquidity because it attracts traders to their markets. Regulators like liquidity because liquid markets are often less volatile than illiquid ones" (cf. p.394, Harris, 2003). Liquidity as a central measure for market quality is therefore one of the main criteria for the attractiveness of a trading venue. Liquidity typically involves several dimensions, which Jones (2013) categorizes into dimensions of price, size, and time. He further points out that most liquidity measures, such as spreads and price impact, coincide with measures of execution costs. In that context, there is a difference between explicit and implicit execution costs. *Explicit* execution costs include broker commissions, exchange fees, and taxes (e.g. transaction taxes). *Implicit* execution costs are more difficult to measure and include e.g. bid-ask spread, depth, market impact, and timing risk among others (p. 284, Aldridge, 2010).

The **Quoted Spread** is an ex-ante measure of liquidity which can be calculated directly from order book data. However, it only measures the transaction costs of small trades at the best (visible) price levels of the order book, thus only representing the transaction costs of small trades. The quoted spread can also be calculated as trade-time quoted spread (Quoted Spread Trade), i.e. the prevailing quoted spread at the time when a trade occurred. Let $Ask_{i,t}$ denote the ask price for a stock i at time t, $Bid_{i,t}$ the respective bid price, and $Mid_{i,t}$ the midpoint. The quoted spread is then calculated as follows:

$$QSpread_{i,t} = (Ask_{i,t} - Bid_{i,t}) / (2 * Mid_{i,t}) \times 10{,}000 \tag{2.1}$$

The **Effective Spread** is an ex-post measure which can be obtained from actual trade and quote data. It represents the actual transaction costs paid when an incoming market order is executed against a limit order. With most data sets, the trade direction of the order has to be inferred from a heuristic (e.g. Lee and Ready, 1991). Let $Price_{i,t}$ denote the execution price and $D_{i,t}$ the trade direction, with -1 for a market sell and +1 for a market buy order, then the effective spread is calculated as follows:

$$ESpread_{i,t} = D_{i,t} * ((Price_{i,t} - Mid_{i,t})/Mid_{i,t}) \times 10{,}000 \tag{2.2}$$

The effective spread can be decomposed into the **Realized Spread**, i.e. liquidity suppliers' revenue, and the **Price Impact** after time x (the latter is discussed in the next section on price efficiency measures). Time intervals x of 5 and 15 minutes are most common. *Realized Spread* equals losses of the market marker to better informed traders and is defined as follows:

$$RSpread_{i,t} = D_{i,t} * ((Price_{i,t} - Mid_{i,t+x})/Mid_{i,t}) \times 10{,}000 \tag{2.3}$$

As Jones (2013) points out, institutions usually "work" large orders over time, i.e. they split large orders into smaller ones that they execute over time in order to reduce price impact, but thereby bear execution risks. To measure the performance of executing these strategies with respect to trading costs and market impact, they use e.g. benchmark strategies, such as the value-weighted average price (VWAP), time-weighted average price (TWAP), Implementation Shortfall (IS).

The *VWAP* is a standard benchmark which is a purely cost-minimizing algorithm and is defined as $VWAP_i = \sum_t v_{it} p_{it} / \sum_t v_{it}$, $t \in T$ where v_{it} is the traded volume of security i at time t, and p_{it} is the market price of security i at time t on day T.

The *TWAP* is another measure for the ability to time the market and is defined as the average price for equally spaced time intervals, i.e. $TWAP_i = (1/T) \sum_t p_{it}$, $t \in T$ where p_{it} is the market price of security i at time t on day T.

The *IS* "measures the efficiency of executing investments decisions" and is computed as the "difference between the realized trades and the trades recorded in paper trading", the latter meaning a record of all trades as if they were "executed at desirable price at optimal times", following Perold (1988).

One example for a more dynamic participation-oriented strategy which is also commonly applied by practitioners is one based on average daily volume (ADV) which aims at executing a certain percentage of daily market volume.

While spread measures account for the width of liquidity, **Depth** is another dimension of liquidity. It measures the quoted volume of limit orders in the order book at a given price (cf. Barclay et al., 2003). Let $VolBid_{i,t}$ and $VolAsk_{i,t}$ denote the volume at the best bid and ask, respectively. *Depth* at the best bid and ask can then be measured as:

$$Depth_{i,t} = (VolBid_{i,t} + VolAsk_{i,t})/2 \tag{2.4}$$

While liquidity in terms of transaction costs has improved, depth decreased (Chordia et al., 2011) which can be accounted to decreases in tick size. This decrease likely contributed to the further decrease in trade size.

Price Discovery

The **Price Impact** measure makes use of continuous price discovery in financial markets and measure the information content of trades and quotes by the price development after their submission. The simple measure *Price Impact* can interpreted as the short-term profit of a trade and is defined as:

$$PImpact_{i,t} = D_{i,t} * ((Mid_{i,t+x} - Mid_{i,t})/Mid_{i,t}) \times 10{,}000 \tag{2.5}$$

However, *Price Impact* (as well as the corresponding *Realized Spread*) only considers one specific price 5 and 15 minutes after a trade. This time interval might be too long for very actively traded stocks, for which a shorter time interval can be assumed to impound new information in the prices, while 5 or 15 minutes might be too short for stocks that are only traded several times a day.

Easley et al. (2012) suggest that "in a high frequency world, trade time, as captured by volume, is a more relevant metric than clock time". Thus, they propose a new framework based on volume imbalance and trade intensity which is measured in volume time, namely the volume-synchronized probability of informed trading (VPIN), or the VPIN flow-toxicity metric. However, its predictive capability on short run volatility has been questioned by Andersen and Bondarenko (2013).

Next to price impact measures, there are econometric techniques to measure deviations from the efficient price and thus price efficiency. These have been analyzed by Hasbrouck information measures (cf. Hasbrouck, 1991b,a). The information measures are based on a pre-defined number of quote revisions after a trade and trades after a quote revision, defined as the number of lags. They therefore take the actual trade activity of the specific stock into account instead of a fixed time interval. Hasbrouck (1991a) uses a vector autoregressive model (VAR) with 10 lags:

$$\begin{aligned} r_t &= \gamma_{0,r} + \sum_{i=0}^{10} \alpha_{t-i} x_{t-i} + \sum_{i=1}^{10} \beta_{t-i} r_{t-i} + u^r \\ x_t &= \gamma_{0,x} + \sum_{i=1}^{10} \delta_{t-i} x_{t-i} + \sum_{i=1}^{10} \eta_{t-i} r_{t-i} + u^x \end{aligned} \tag{2.6}$$

with r_t as the time series of quote revisions and x_t the time series of trade direction. γ, α, β, δ, and η are the coefficients of the respective VAR models, and u^r and u^x are the error terms. The quote revision r_t is decomposed into ten preceding trades $x_t - 10, ..., x_t$, ten preceding quote revisions $r_t - 10, .., r_t$, as well as the mean γ and the error term u_r. The cumulative impulse response function is the result of the inversion of the VAR-model to a vector moving average (VMA) representation and the addition of the coefficients of the VMA model. The cumulative impulse response function can be interpreted as the information impact of 10 preceding trades on the current quote.

In order to highlight the different regimes of market quality in the last decades, a comparative case study of the two prevailing electronic market systems in Germany at that time, IBIS II and Xetra, is conducted.

2.1.2 Market Quality Framework

Improvements in market quality can be attributed to several factors that are external and internal to markets. In the context of this framework for market quality as depicted in Figure 2.1, external factors influence market quality indirectly and cannot be influenced directly by trading venues. External factors include technological development as well as the regulatory and competitive environment. On the other side, internal market structure concerns how the market is designed, created, and operated, and is also often impacted by changing external factors.

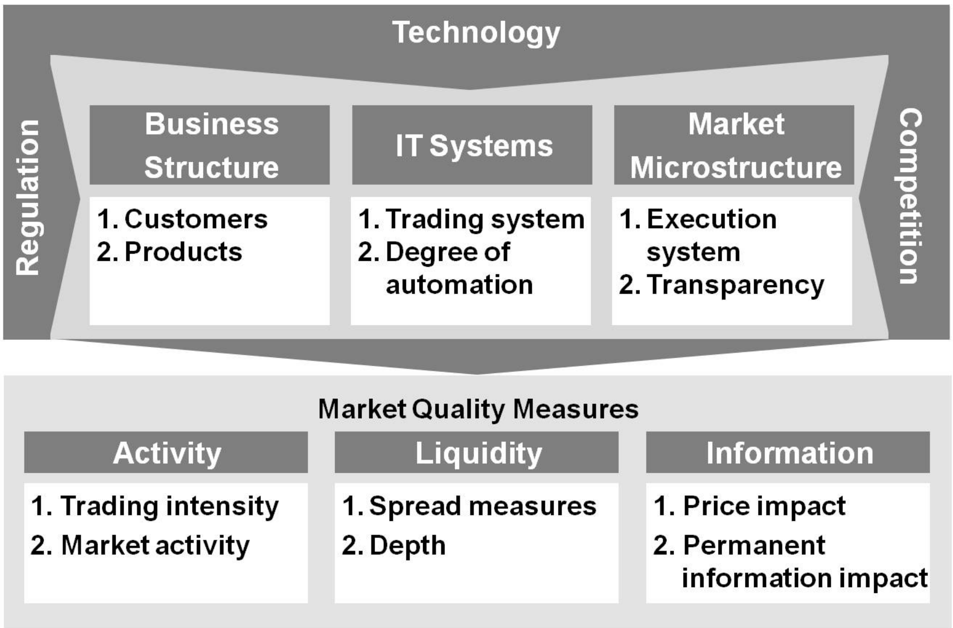


Figure 2.1: Framework for Market Quality

Technological Innovation

The last years have seen an unprecedented development in computing power and network systems which linked computers globally. This development has profoundly changed several aspects in the financial trading landscape which has been extensively studied. Important technological aspects include automation, such as the introduction of electronic trading, speed which includes latency reductions in the form of system updates as well as investment into faster technology, AT and HFT, and automated information processing.

Literature has found different effects of the use of automation in financial markets on transaction costs and cost of capital. Venkataraman (2001) finds higher execution costs on the automated trading floor in Paris than for floor trading on the NYSE, pointing towards some beneficial elements of human intermediation. Jain (2005) studies the impact of automation by the introduction of electronic trading and finds improvements in liquidity, informativeness, and reduced cost of capital. Easley et al. (2013) analyze a major system upgrade at NYSE in 1980/1981 which enhanced system latency and improved information dissemination. They find significant price improvements for stocks traded by posts that experienced an extended latency reduction as well as reduced transaction costs in the low latency regime. Hendershott and Moulton (2011) examine the introduction of the hybrid system at NYSE which reduced latency and improved electronic order execution. They find increased bid-ask spreads due to increased adverse selection by anonymous trading as well as higher price efficiency. Riordan and Storkenmaier (2012) study a upgrade of the Xetra system at Deutsche Börse which involved a latency reduction and led to a decrease in quoted and effective spreads. Other papers concentrate on the relevance of geographical distance to the market venues. Hau (2001) finds that higher geographical distance lowers proprietary trading profits. Garvey and Wu (2010) find that orders of traders located in the NYC area are executed at a significantly better price than orders of traders outside the NYC area.

More recent technological trends include the automated processing of information and the impact of automated news on market quality. Gross-Klussmann and Hautsch (2011) show that there are significant intraday effects around the arrival of stock-specific Reuters news ticker information. In Riordan et al. (2013), we show that there are asymmetric effects of positive and negative stock-specific information on market quality. The increasing relevance of social media has become apparent when a fake tweet resulted in a stock market plunge. This tweet about a bombing in the White House which was the result of a Twitter hack on April 23, 2013 led to plunges in the stock markets and a 143 fall in the Dow Jones industrial average (The Guardian, 2013). A survey on social media in trading by One Market Data LLC, a firm specialized in tick data management and analytics, stated that this event "revealed potential weaknesses in social media's usability to feed trading and investment strategies, but it also demonstrated the impact the new form of data already is having on financial markets" (One Market Data, 2013). As a result, 18% of survey participants said the they are currently using social media data for trading, while 35% said that they were researching into how to incorporate social media into trading strategies. With the increasing relevance and interest of investors in social media, the demand for solutions to use social media data will also be expected to grow, the director of solutions at OneMarketData states.

Regulation and Competition

Regulatory authorities have tried to keep pace with new technological advances of electronic markets and different market environments by adapting new regulation. During the last years, one of the regulatory changes with the biggest impact on trading in Europe includes the "Markets in Financial Instruments Directive" (MiFID). MiFID became effective in November 2007 to create a harmonized trading landscape in the 27-nation European Union. It abolished the concentration rule which favored one single dominating exchange in each country. Instead, MiFID promotes competition between traditional exchanges and multilateral trading facilities (MTF) and the order processing under best execution. Best execution under MiFID relies on multiple factors, for instance prices, trading costs, speed, or likelihood of execution and settlement. The introduction of MiFID allowed MTFs to offer trading in European equities, which led to fierce competition between trading venues in Europe. After this regulatory change, the till then monopoly-like status of traditional exchanges has evolved to a more fragmented and diverse European market.

Literature is inconclusive about the impact of market fragmentation and competition on market quality and price discovery. Barclay et al. (2003) explore the competition of Electronic Communication Networks (ECNs), a form of Alternative Trading System (ATS) in the US, and NASDAQ market makers. They report that trades are more likely to be executed on ECNs in case of high information asymmetry, high trading volume and stock-return volatility. However, ECNs possess higher execution costs, since NASDAQ market makers can preference or internalize less informed trades. Degryse (2009) provides a review of the theoretical and empirical literature on intermarket competition and discusses implications in the European case of MiFID. Gomber and Gsell (2006) discuss possible regulatory changes of MiFID in the context of technological advances and best execution. Empirical studies include Hengelbrock and Theissen (2009) and Storkenmaier et al. (2012). Hengelbrock and Theissen (2009) study the market entry of Turquoise in 14 different countries in September 2008 and find that the "entry of Turquoise led to a decrease in spreads but not to an increase in trading volume". Storkenmaier et al. (2012) study public information arrival on London Stock Exchange (LSE) and Chi-X post-MiFID and find that private information shifts from Chi-X to the LSE on both positive and negative days.

Internal Microstructure, Business Structure, and IT Infrastructure

In contrast to external factors, the internal market structure directly influences market quality. External factors provide general conditions which affect the internal market structure, i.e. the design, creation, and operation of electronic markets. Following Weinhardt et al. (2003), the internal market structure can be decomposed into business structure, market microstructure, and IT systems.

At the heart of market design, the microstructure is established. Market microstructure is "the study of the process and outcomes of exchanging assets under explicit trading rules" (p.1, O'Hara, 1997). In order to determine the market microstructure, the execution system, the market model, and the role of intermediaries have to be defined, as well as the degree of transparency. Changes in microstructure can have a direct effect on market quality, which has been one focus in market microstructure research.

The market model determines the auction model of the market, for example a call auction or a continuous double auction, which also are the two most important ones for financial markets.

The execution system, i.e. the matching of buyers and sellers, can be either quote-driven, brokered or order-driven, or a hybrid form of those. Quote-driven and brokered markets involve intermediaries, e.g. in the form of brokers or liquidity providers. One prominent example for a comparison of execution systems is presented by Huang and Stoll (1996). They analyze differences in liquidity of the NASDAQ, and the NYSE. During their observation period, the NYSE operated a floor-based order-driven trading system, but also engaged liquidity providers in the form of specialists. Those are more common in quote-driven systems. The NASDAQ, on the other hand, was a fully quote-driven market at that time, with dealers acting as intermediaries for every trade. Huang and Stoll (1996) compare both execution systems and find that transaction costs on the NASDAQ are larger than on the NYSE.

Another aspect of market microstructure is the degree of transparency, i.e. the extent to which information is disclosed before, during, and after the trading process plays a vital role. Boehmer et al. (2005) examine the introduction of the NYSE's OpenBook, the dissemination of the whole order book instead of only the best bid and ask prices. This increase in pre-trade transparency has led to changes in market quality: smaller order sizes, more order cancellations, less order book depth, liquidity improvements, and a decline in the participation of specialists.

Depending on the customer target group, trading venues adapt their market model to cater to a specific business structure. Among others, it specifies a target group of customers that the market intends to attract and provide products and services for. Different types of traders are attracted by different market models, making the choice of market model and the knowledge of trader types extremely relevant.

The close connection of business structure and IT systems can be demonstrated by the example of AT and HFT systems. Agency AT strategies are usually applied to split large orders into smaller ones in order to minimize impact and transaction costs and to hide information and trading strategies. AT systems with short-term strategies, called HFT systems, intensify this effect even more.[1] HFT strategies sometimes involve the submission and an immediate cancellation in case of non-execution of an order, both within milliseconds. As a result, increased trading and quoting activity, and a rising demand for speed and anonymity can be observed. With this changing group of customers, exchanges adapted their IT system and business structure accordingly. However, ECNs und MTFs often meet the described needs of traders for anonymous low latency systems better than traditional exchanges.

On the other side however, foreign exchange markets such as ICAP's EBS chose to curb HFT activity on their platform by introducing a "latency floor" for specific currency pairs, meaning that orders are bundled into batches of one to three millisec-

[1] For a more detailed distinction of AT and HFT systems, see Section 2.2.1.

onds and executed in a randomized fashion (cf. Reuters, 2013a). With this change in microstructure, they intend to level the playing field for both HFT and non-HFT groups.

2.1.3 Case Study: IBIS vs. Xetra

A comparative case study of the IBIS II and the Xetra system serves as a demonstration of the evolution of market quality over time and an exemplary application of the market quality framework. Both were two predominant financial electronic markets in the history of German exchanges. IBIS II had been the trading system for German DAX 30 securities between April 1991 and November 1997. It has been replaced by the Xetra system in November 1997.

Institutional details

The “Inter-Banken-Informations-System” (IBIS I) was originally designed as a quotation and settlement support system for the Deutsche Boerse Group. The Deutsche Boerse Group is one of the largest stock exchange operators in the world. In the early days between December 1989 and April 1991, trading took place from 8:30 a.m. to 5 p.m. (local time) by phone. IBIS I was replaced by the “Integriertes Boersenhandels- und Informationssystem” (IBIS II), a fully automated trading system organized as an anonymous continuous open limit-order book with price-time priority. However, it was only possible to trade round lots of 100 or 500 shares (cf. Schmidt and Iversen, 1992; Theissen, 2002, for details). Orders were directly transferred to the DWZ, the German securities clearing service.

The Deutsche Boerse Group replaced IBIS II with the Xetra system in November 1997, the prevailing trading system for all German securities since, which has undergone several releases and changes. The Xetra system is a fully-electronic trading system, with trading hours from 9:00 a.m. (local time) to 5.30 p.m. (local time) in the chosen sample. Like IBIS II, it is order-driven, anonymous, and is organized as an open limit-order book. It follows a flexible market model, specifically a continuous double auction. There is an opening call auction at 9:00 a.m. (local time) in the morning, a two-minute intra-day call auction at 1:00 p.m. (local time) and a closing call auction at 5:30 p.m. (local time), all three with a random ending. This study focuses only on the continuous trading periods.

The external factors, i.e. regulation, competition, and technology significantly changed over time. In contrast, the basic market microstructures of IBIS II and the Xetra system as described above are quite similar: Both enable fully automated continuous trading with price-time priority within same time durations. The analysis primarily focuses on the comparison of both markets with regard to the specified market quality measures and to the external factors and internal market structure of the market quality framework.

The data samples used in the case study consist of DAX stocks traded on IBIS II between January 1st, 1997 and March 31st, 1997 and on the Xetra system for the same time period in 2009. Table 2.1 shows the data samples, with each consisting of 29 DAX stocks. Companies that are not continuously traded during the observation period are excluded. The companies in Table 2.1 are ranked by their average daily trading volume over the specific observation periods. While Sample 1 consists of stocks traded on IBIS II, Sample 2 comprises Xetra stocks. In order to transform measures given in Deutsche Mark from Sample 1 to Euros, the exchange rate at which the currency entered the Euro is used.

Internal and External Changes

Despite the similar market microstructure of both markets, internal and external factors have significantly changed. The external factors regulation and competition have profoundly changed from 1997 to 2009 particularly after the introduction of MiFID. As a result of the concentration rule, national markets have often operated as a de facto monopolist. After MiFID, the introduction of MTFs has started a fierce competition for order flow between incumbent exchanges in Europe and alternative trading venues. For instance the London Stock Exchange (LSE) lost over 30 percent of its market share between 2007 and 2009. Deutsche Boerse has been able to maintain a higher fraction of market shares but they have also seen a significant drop lately. As to the

Table 2.1: Sample Constituents
The table presents sample constituents for DAX stocks traded on IBIS II between January 1st, 1997 and March 31st, 1997 and on the Xetra system for the same time period in 2009. The trading volume categories are obtained by ranking the firms in the DAX by their average daily trading volume for the IBIS II and Xetra samples. The values are reported in millions. The first category contains the first 15 firms with the highest trading volume (High) and the second the next 14 firms (Low).

	Sample 1: IBIS II 1-Jan-1997 to 31-Mar-1997		**Sample 2: Xetra 1-Jan-2009 to 31-Mar-2009**	
	Firm	**Volume**	**Firm**	**Volume**
	High Volume Stocks			
1	Dt. Bank	101.42	Dt. Bank	205.42
2	Siemens	94.59	Siemens	196.56
3	Daimler Benz	94.25	Allianz	172.51
4	Volkswagen	71.46	Eon	172.06
5	Hoechst	56.55	Dt. Telekom	161.08
6	Bayer	49.40	Bayer	142.95
7	BASF	48.06	Daimler	131.17
8	VEBA	46.06	RWE	126.85
9	Dt. Telekom	39.17	SAP	116.41
10	Mannesmann	38.86	Muenchener Rueck	109.80
11	Allianz	35.67	BASF	98.62
12	Commerzbank	28.09	Volkswagen	92.24
13	SAP	25.63	BMW	63.62
14	BMW	21.29	Dt. Boerse	57.05
15	Dresdner Bank	17.51	Thyssen Krupp	50.87
	Low Volume Stocks			
1	RWE	16.92	Dt. Post	43.32
2	VIAG	15.61	K+S	43.27
3	Schering	14.14	Linde	41.69
4	Bay. Vereinsbank	10.52	Commerzbank	39.03
5	Metro	10.33	Fresenius Medical	33.91
6	Bay. Hypo	10.08	MAN	33.60
7	Muench. Rueck	9.30	Adidas	28.22
8	Preussag	8.84	Salzgitter	26.79
9	Dt. Lufthansa	8.19	Merck	24.96
10	MAN	5.91	Metro	24.46
11	Henkel	5.86	Dt. Lufthansa	24.41
12	Linde	5.09	Beiersdorf	20.07
13	Degussa	4.97	Henkel	16.72
14	Karstadt	4.74	Fresenius	14.97

technological changes, there is an immense increase in the speed of both information and communication technology. The electronic revolution has also greatly affected the German trading landscape, with the use of computerized high speed trading systems, geographically dispersed market participants, anonymization of trading, and a greater choice of trading platforms.

The change in external factors has triggered a substantial transformation of exchanges' internal market structures consisting of business structures, IT systems, and market microstructures. The customer target group as an aspect of the internal business structure has changed. Particularly institutional investors aim for more sophisticated trading strategies and a higher degree of automation, e.g. by using algorithmic trading systems. With the introduction of the Automated Trading Program (ATP) in December 2007, Deutsche Boerse directly targets to attract algorithmic traders. ATs have a different trading behavior than human traders as well as competitive advantage with respect to speed and computation, as pointed out by Hendershott et al. (2011). Therefore, the importance of latency and availability have changed. Nowadays, trading venues compete for customers by offering co-location services and faster systems.

The aforementioned development has been enabled by increasingly automated IT systems and it has also been accompanied by a shift from floor to electronic trading. In 1997 floor trading still played an important role, leaving IBIS II with about 40 percent of the total trading volume in DAX stocks. The situation in 2009 was quite different. Xetra now accounts for more than 90 percent of turnover in the DAX shares. IBIS II and Xetra are based on different IT systems. Xetra was originally developed to attract order flow from non-institutional investors and from outside of Germany by providing a decentral access. Since it was accessible for all market participants, it also provided improved transparency, which is part of the market microstructure.

Changes in Market Quality

All these changes in the business structure and in IT systems led to an anonymous and highly automated market which has been faster in processing trades and trade information. There is no change in the main characteristics of the market microstructure. However, main drivers of a market differences between Xetra and IBIS II can be attributed to the internal factors business structure and IT structure strongly driven by changes in external factors. For the evaluation and comparison of market quality of both markets, descriptive statistics of market quality measures are reported in Table 2.2.

Table 2.2: Descriptive Statistics

Table 2.2 provides market activity, liquidity, and information measures for DAX stocks traded on IBIS II between January 1st, 1997 and March 31st, 1997 (Sample 1) and on the Xetra system for the same time period in 2009 (Sample 2). The mean, the standard deviation as well as minimum and maximum values of all measures are reported on a daily basis per instrument. *Turnover* is the average daily trading volume in million Euros, *TradeCount* the average number of trades per day, *TradeSize* the average trading volume in Euros per trade, and *Quotes* the total number of price and volume updates per day. In order to transform measures given in Deutsche Mark from Sample 1 to Euros, the exchange rate at which the Deutsche Mark entered the Euro is used. For the liquidity and information measures, I report different spread measures as relative measures in basis points. While the $QSpread$ is the quoted spread calculated on a tick-by-tick basis per instrument, $QSpreadTrd$, $ESpread$, $RSpread5$, and $RSpread15$ are reported trade-by-trade. $RSpread5$ ($RSpread15$) uses the midpoint in t plus 5 minutes (t plus 15 minutes) as reference point. *Depth* gives the daily average quoted volume at the best bid and ask in Euros for all data set entries. Daily average price impacts are calculated using midpoints as reference points in t plus 5 minutes (t plus 15 minutes) for $PImpact5$ and $PImpact15$, respectively.

	Sample 1: IBIS II 1-Jan-1997 to 31-Mar-1997				**Sample 2: Xetra 1-Jan-2009 to 31-Mar-2009**			
	Mean	**Std**	**Min**	**Max**	**Mean**	**Std**	**Min**	**Max**
				Trading Intensity				
Turnover	30.983	35.543	0.972	464.663	79.746	70.764	5.983	672.762
Trd Count	228	202	10	3,060	4,314	2,779	632	25,228
Trd Size	124,993	67,479	29,293	386,888	16,295	6,090	5,302	38,504
Quotes	654	418	74	5,243	43,301	28,105	4,601	265,501
				Liquidity				
QSpread	14.386	8.784	2.996	66.990	6.440	2.461	2.447	18.758
QSpr Trd	11.333	6.808	2.506	53.125	5.179	2.028	2.011	18.055
ESpread	11.344	6.813	2.494	53.125	3.936	1.667	1.489	14.616
RSpread5	2.588	4.929	-14.140	34.588	1.284	1.507	-5.864	11.994
RSpread15	1.615	5.834	-22.216	35.485	1.380	2.407	-8.408	21.513
Depth	151,261	69,601	38,513	414,371	31,579	18,507	12,783	144,444
				Information				
PImpact5	8.814	5.009	1.251	42.955	2.701	1.552	-1.683	11.914
PImpact15	9.803	6.888	-3.904	49.162	2.604	2.415	-13.812	15.926

In contrast, the number of trades has shown an 18-fold increase, from 228 trades per day to 4,314 trades. The explanation comes with the analysis of average trade sizes, which are in 2009 less than one seventh of the sizes they were in 1997. This accounts for the small increase in turnover relative to the immense increase in the number of trades. The standard deviation is 67,479 Euros compared to 6,090 Euros, indicating that the main part of the order flow concentrates in the dimension of small orders. Thus, the behavior of traders has dramatically changed within the time period between 1997 and 2009.

Market activity in general is reflected by quote updates, which occur with every cancellation of an order, a change of best bid, ask or volume, as well as the execution of an order over one or more levels in the order book. Quote updates have increased with the factor 65, from 654 updates to 43,300 updates. A large proportion of these changes in activity can be attributed to recent technological developments like algorithmic trading and low latency networks. Today, large orders are often split into smaller ones in order to minimize their impact and to hide the trading strategy which leads to more and smaller trades.

Regarding the liquidity measures, there is a decrease of up to 65 percent, from 11.34 bps to 3.94 bps for average effective spreads and from about 11.33 bps to around 5.18 bps in the case of average quoted spreads at trades, with smaller standard deviations and therefore a lower variability in the availability of liquidity. This increase in liquidity might be explained by higher competition between liquidity suppliers in the order book. On the other hand, depth has fallen quite sharply, from 151,261 to 31,579 Euros on average per day and instrument. However, this development can be explained by changes in trading behavior and strategies. As stated before, order sizes have decreased on average, thus one might infer smaller orders at the best bid and asks.The results imply that there is an improvement of liquidity in spread measures, but not a definite improvement of overall liquidity. Spreads decrease, implying a higher liquidity, depth on the other side decreases, implying a lower liquidity. Such results are also reflected in MiFID's best execution policy which requires intermediaries to consider multiple dimensions of market quality (cf. Section 2.1.2).

The information content of trades, measured by the price impact, decreased between 1997 and 2009, with a simultaneous increase of realized spread. The results show that the price impact at the five minute mark decreases from 8.814 bps to in 1997 only 2.701 bps in 2009. As expected, information per trade decreases as a result of smaller order sizes and increased activity as shown in the descriptive results for market activity. Thompson clustered standard errors (cf. Thompson, 2011) are applied to test for the statistical significance of the differences. Each sample is split into high and low volume stocks and test these categories individually.

The results shown in Table 2.3 are statistically significant at the 1% level for quoted, effective and realized spreads and price impacts at the 5-minute mark. Individual trades have a larger price impact both in 1997 and 2009 for low volume stocks. Differences between trades of less than 4000 shares and more than 4000 shares are generally more pronounced on the Xetra system.

In conclusion, quantitative measures and qualitative aspects have tremendously changed. Overall, there is a significant increase in activity and liquidity, with significant decreases in effective spreads, actual transaction costs, from 1997 to 2009. While the landscape of external factors, regulation, competition, and technology have necessarily changed due to the computerization of financial markets, the internal market structure has also been adopted, by providing higher transparency and focusing more on the needs of AT and HFT.

2.2 Economic and Regulatory Aspects of HFT

The growing importance of AT and HFT has gained considerable attention in public and regulatory discussions in recent years. However, due to the variety of different HFT strategies, definition of the term HFT vary considerably. In this section, I give insight into the term HFT which is usually defined by specific trading characteristics and strategies. I further discuss the growing body of related literature especially in the light of market quality effects and ongoing regulatory proposals and actions against the negative effects of HFT and further present some descriptive measures of HFT contribution to liquidity in the case study "HFT and liquidity".

Table 2.3: Liquidity and Information Measures over time

Table 2.3 reports tests for differences in *Quoted Spread*, *Effective Spread*, *Realized Spread*, and *Price Impact* for DAX stocks traded on IBIS II between January 1st, 1997 and March 31st, 1997 and on the Xetra system for the same time period in 2009. The trading volume categories are obtained by ranking the firms in the DAX by their average daily trading volume for the IBIS II and Xetra sample. The first category contains the first 15 firms with the highest trading volume (High) and the second the next 14 firms (Low). While *Quoted Spread* is calculated on a tick-by-tick basis per instrument, *Effective Spread*, *Realized Spread 5*, and *Price Impact 5* are calculated on a trade-by-trade basis. All measures are given on a daily basis per instrument and calculated as relative measures in basis points. In addition, trade based measures for trades with less than 4,000 shares and equal or greater than 4,000 shares are reported separately. To test for differences between the IBIS II and Xetra sample, I match stocks according to their average daily trading volume over the sample periods, i.e. the two DAX stocks with the highest trading volume build the first stock pair, the second pair consists of the stocks with the second highest trading volume, and so on. Thompson clustered standard errors are used to test for differences in measures between IBIS II and Xetra and report the corresponding t-statistics and significance levels. *** denotes significance at the 1% level and ** at the 5% level.

Trade Size	**High Volume Stocks**				**Low Volume Stocks**			
Category	**IBIS II**	**Xetra**	**Diff**	**t-stat**	**IBIS II**	**Xetra**	**Diff**	**t-stat**
				Quoted Spread				
All	9.313	5.363	3.950	4.100***	19.821	7.595	12.226	6.311***
				Effective Spread				
All	7.411	3.353	4.058	5.756***	15.557	4.560	10.997	6.734***
< 4000	7.359	3.352	4.008	5.605***	15.541	4.567	10.974	6.698***
>= 4000	6.419	4.346	2.073	4.505***	13.153	6.289	6.864	3.944***
				Realized Spread 5				
All	0.362	1.163	-0.801	-3.261***	4.973	1.414	3.56	3.577***
< 4000	0.595	1.174	-0.579	-2.369**	5.156	1.46	3.696	3.745***
>= 4000	-0.393	1.017	-1.410	-2.723***	0.783	-0.193	0.976	0.761***
				Price Impact 5				
All	7.090	2.235	4.855	7.765***	10.660	3.201	7.460	10.023***
< 4000	6.804	2.223	4.581	6.900***	10.458	3.162	7.296	9.566***
>= 4000	6.863	3.761	3.102	4.495***	12.463	7.171	5.292	2.609***

2.2.1 HFT Definition and Strategies

HFT can be considered as a subcategory of AT which is commonly defined as the use of computer algorithms to support the trading process (cf. Hendershott et al., 2011). While popular AT algorithms are simple transaction cost minimizing algorithms, so-called "slice and dice" algorithms, which split large orders into smaller ones in order to minimize price impact and transaction costs (c.f. Gomber and Gsell, 2006), HFT algorithms are often more complex. Since HFT involves different trading strategies, there is no specific HFT definition, but trading characteristics that constitute such a group of high-speed traders that academics and regulator focus on. The SEC identifies the following characteristics (cf. p.45, SEC, 2010):

1. extraordinarily high-speed and sophisticated computer programs for generating, routing, and executing orders;
2. use of co-location services and individual data feeds offered by exchanges and others to minimize latency;
3. very short time-frames for establishing and liquidating positions;
4. submission of numerous orders cancelled shortly after submission; and
5. ending the trading day in as close to a flat position as possible (that is, not carrying significant, unhedged positions over-night).

Further characteristics include high message rates in terms of order submissions and cancellations (a direct consequence of characteristic 4) which poses a substantial burden to market venues in term of processing power. Jones (2013) illustrates three groups of HFT strategies, namely market making, relative-value trading (arbitrage), and directional trading. I follow this classification and further discuss another loosely defined group of manipulative trading strategies that makes use of weaknesses of other participants and of structural nature of the market and thus especially concern regulators. The SEC similarly categorizes HFT strategies into four groups (namely passive market making, arbitrage, structural, and directional strategies) and point out possible negative effects on financial markets for each group (SEC, 2010).

Automated Market Making

Market making strategies involve liquidity provision by the submission of non-marketable resting orders (bids and offers) that provide liquidity to the marketplace at specified prices. On the other side, liquidity takers submit marketable orders, i.e. market orders or limit orders that can be executed directly against orders in the order book. Market-makers aim to buy at the bid price and sell at the ask price and thereby make the bid-ask spread as a profit. They further profit from liquidity rebates provided by marketplaces. While the classic structure involves a fee for every transaction, there has been a shift to rebate pricing. Rebate pricing grants liquidity providers a rebate, while liquidity takers pay a fee. The impact of the introduction of a maker-taker rebate system is analyzed by e.g. Malinova and Park (2011).

What is questioned is the quality of liquidity provided since algorithms often cancel limit orders immediately after submission. This would result in a "flickering" of liquidity for a few milliseconds, but no liquidity that non-HFT can actually use. Since the rebates for liquidity provision are often only fractions of a basis point, passive market making strategies involve a high amount of trading volume and a fast connection to be profitable. Another point of discussion is the fairness against other long-term investors who cannot profit from this kind of rebate to the extent that HFTs do. Further questions are whether marketplaces should adopt their business structure and also request certain trading obligations to grant this kind of rebate.

Arbitrage Trading

Arbitrage strategies seek to profit from pricing inefficiencies between related products or same products on different markets by selling the overpriced and buying the underpriced instrument or sell at the market with the higher price and buy at the market with the lower price respectively. HFT have the possibility to make use of arbitrage opportunities that only exist for a few milliseconds. A popular strategy is index arbitrage which can involve different instruments based on the same underlying (e.g. the S&P 500 futures and the exchange-traded fund (ETF) that tracks the S&P 500 index) or index products and individual stocks that make up the index

(Jones, 2013). Another typical arbitrage strategy is pairs trading which makes use of statistical correlation of securities. It usually involves quantitative and heavily computational approaches, which can be better solved by computers than humans. The impact on market quality here is of a positive nature, since the detection of arbitrage improves price efficiency and market quality.

Directional Trading

Another strength of HFT systems involves the processing of considerable amounts of possibly complex data sources, such as macroeconomic announcements, textual news information, or historical transaction data (cf. Section 3). As in Aldridge (2010, cf. p.16), directional strategies identify short-term trends or momentum. While the group of event-driven directional strategies might be beneficial for financial markets, there might also be manipulative ignition strategies. Automated news trading involves the analyses of market and investor sentiment, semantic analysis, and text mining, which are only a few examples of the ongoing research being conducted to make texts or qualitative financial data interpretable for machines. As introduced by Martinez and Roşu (2013), the dimension of "information precision" plays a crucial role for this type of information processing strategies.

Market Manipulation

Manipulative strategies include the exploitations of certain vulnerabilities of markets and participants and are often called predatory strategies. Latency Arbitrage, Order Anticipation, and Momentum Ignition strategies are often mentioned that would cause potential harm to financial markets (SEC, 2010), but also other strategies are listed as potential abusive types of strategies (e.g. Biais and Woolley, 2011; IIROC, 2012).

- *Latency Arbitrage* makes use of the low-latency nature of HFT (use of co-location and high-frequency data feeds) and is a concern in terms of a structural abuse of RegNMS. Since a National Best Bid and Offer (NBBO) system provides an official efficient price, HFTs could construct their own NBBO using their high-frequency data feeds which is faster than the official NBBO and thus trade on these stale prices as compared to their own faster and more efficient price (cf. p. 52f., SEC, 2010).

- *Order Anticipation* involves the detection of large orders, e.g. using sophisticated pattern recognition or "pinging" different market centers, and trade ahead of these orders. This type of detection activities might be perceived as some sort of front running, which however does not involve the use of confidential information, but the use of "pinging" strategies (i.e. the use of very small orders which indicate the existence of hidden orders for example). While order anticipation strategies specifically harm the investor whose order is being anticipated, they do not improve market quality in any way. It is still an open question whether and how these large orders are strategically disadvantaged in their execution by HFTs.

- *Momentum Ignition* or "Layering" strategies aim to ignite a rapid price movement in one direction by a series of orders and traders. While other traders follow the price movement, HFTs would take the other side of the market and profit from the artificially high or low prices. This kind of market manipulation would harm market quality by increasing market inefficiency.

- While ignition strategies using trades carry a certain amount of risks, *Spoofing* strategies usually include the submission of limit orders that are not intended to be executed in order to manipulate prices.

- *Smoking* strategies similarly involve alluring limit orders to attract slow traders. Then HFT would rapidly revise these orders with less favorable prices to profit from incoming flow of slow traders' market orders (Biais and Woolley, 2011).

- *Quote Stuffing* involves a huge number of orders and cancels in order to strategically slow down the matching engines and increase latencies, possibly in order to create "latency arbitrage" opportunities (IIROC, 2012).

2.2.2 HFT Literature

The body of HFT literature has been growing in the recent years. While the empirical work has concentrated mostly on the overall impact of HFT on market quality in terms of liquidity, price discovery, and efficiency, the theoretical work was able to give more detail on the specific trading characteristics, such as the speed advantage or news trading strategies, and their influence on market quality and welfare.

Theoretical HFT Literature

The specifically HFT-related theoretical papers are Biais et al. (2012), Jovanovic and Menkveld (2012), Martinez and Roşu (2013), and Foucault et al. (2013).

Biais et al. (2012) analyze the number of fast and slow traders in a market as well as the equilibrium investment level of traders into fast technology. Their results yield ambiguous results: While a certain amount of fast traders can increase volume, it might also crowd out slower traders. This ambiguity seems to be reflected in different amounts of HFT in different markets: While equity and futures market venues continue to invest into faster platforms and IT systems, FX market such as EBS (as mentioned above in Section 2.1.2, Reuters, 2013a) experience a crowding out of slower traders. This and a possible "over-investment" into fast trading technology would in fact decrease overall welfare.

Jovanovic and Menkveld (2012) focus on the intermediary "middlemen" role of HFT. They show that HFTs acting as intermediaris can decrease adverse selection by processing information faster and quote more efficiently, and thus improve welfare.

Martinez and Roşu (2013) and Foucault et al. (2013) concentrate on directional information-processing HFTs. Martinez and Roşu (2013) find that with increasing HFT activity, volume and liquidity increases as well as informational volatility and market efficiency due to the faster information processing of HFTs. In Zhang (2013), I test several theoretical predictions of the model empirically and find consistent empirical results. Foucault et al. (2013) further model the effects of information accuracy (or news precision) and speed.

Cartea and Penalva (2011) model a market with liquidity traders, market makers, and HFTs. They find that HFTs increase price volatility, trade volume, and may decrease liquidity.

Empirical HFT Literature

The empirical body of HFT literature concentrates on the influence of HFT on market quality, but also extends to measures of profitability subject to the availability of more detailed data. Brogaard et al. (2013) analyze the impact on price efficiency and find that HFT significantly contribute to informational volatility. Hagströmer and Nordén (2012) analyze different types of HFT strategies, market-making and opportunistic HFTs, and find that market-making HFTs lower short-term volatility. Hasbrouck and Saar (2013) use "strategic runs" (responses to market events in the millisecond environment) as a proxy for HFT activity and find positive effects of HFT on market quality in terms of decreased spreads, increased order book depth, and lower short-term volatility.

Other papers have also shown negative effects of HFT on price discovery and market volatility. Kirilenko et al. (2011) find that HFT did not trigger the "Flash Crash" on May 6th, 2010, but exacerbated market volatility during this extreme event. Hirschey (2013) finds that HFT are better at anticipating buying and selling pressure and order flow. Predatory HFT strategies include quote stuffing, as discussed below, which is analyzed empirically by Gai et al. (2012) and Egginton et al. (2012).

Menkveld (2013) analyzes the trading activity and profit of an HFT market maker who is active on both Chi-X and Euronext. Baron et al. (2012) find that HFTs make $23 million in trading profits in the E-mini S&P 500 futures market in August 2010 and that the fastest HFT firms earn the highest profits.

Research on HFT is also closely related to research on AT. Hendershott et al. (2011) focus on the impact of AT on liquidity and find a positive impact on liquidity, but no increase in volatility caused by AT. On the contrary, they find that an increased activity of AT leads to more efficient prices for large stocks. Chaboud et al. (2013) analyze the effects of AT on volatility in foreign exchange markets. Despite an apparent correlation of high frequency trading strategies, a higher activity of AT is not associated with higher volatility, but an increase in efficiency by the execution of arbitrage strategies. Hendershott and Riordan (2013) find that ATs improve liquidity and specifically that they consume it when it is cheap and supply liquidity when it is expensive. Boehmer et al. (2012) study the introduction of co-location facilities as a proxy for AT activity and find that higher AT activity increases liquidity, informational efficiency, and volatility.

2.2.3 HFT Regulation

Despite the fact that most empirical studies find positive effects of HFT on financial markets, regulators in the U.S. and Europe are discussing stricter regulations for HFT. The concept release on equity market structure published by the SEC (SEC, 2010) highlights some of the regulatory concerns on HFT. The "Flash Crash" on May 6th, 2010, has further fueled the discussions. The more than 10% drop in the Dow Jones Industrial Average has drawn the public's attention to HFT and although HFT seems not to have been the original source of the event, they may have exacerbated the situation (cf. Kirilenko et al., 2011). The increase of market volatility has served more to focus negative attention on HFT.

The MiFID, an EU wide regulation on financial services, is currently under review. One of the focuses of the MiFID review ("MiFID II") and of a new regulation (Markets in Financial Instruments Regulation, MiFIR) is how to regulate HFT. The proposals regarding HFT regulation would have a significant impact on the structure and quality of European financial markets. Regarding the proposals, the Association for Financial Markets in Europe (AFME) published a position paper on the regulatory points of discussion concerning HFT (Association for Financial Markets in Europe, 2012). These are discussed in the context of recent regulatory developments in the U.S. and Europe below:

- Authorization and Risk Control: AFME generally agrees with the European Commission's intentions to increase regulatory oversight of members of trading venues and risk control of clients that have "direct electronic access". With the

HFT act coming into effect in Germany, this would be a first attempt to increase transparency by requiring a license for HFT firms and flagging orders by those firms.

- Direct Electronic Access: This term includes the different forms Direct Market Access (DMA), Sponsored Access (SA), and Naked Sponsored Access. DMA allows automatic transmission of orders to a specified trading platform after being transmitted first to the investment firm's internal electronic trading systems which is often used by smaller brokers and retail investors. SA is defined as direct access without being routed through internal electronic trading systems of the investment firm, but has to pass pre-trade controls of the investment firm. Naked SA would be unfiltered access without any pre-trade controls and is prohibited under MiFID. Thus, DMA and SA serve as valuable services not only to HFT, but also to retail investors in order to reduce transaction fees and to provide cost-effective market access.

- Order-to-Trade Ratios: Several HFT strategies involve a large amount of message traffic in the form of order submissions and cancellations without an appropriate number of actually executed trades. Since the former would not involve any fees for these types of traders, several exchanges have introduced excessive order fees in order to limit these activities. For example, Nasdaq OMX, Borsa Italiana, Oslo Børs and Xetra Frankurt have implemented fees on high order-to-trade ratios (Credit Suisse, 2012). However, the range has been considerably wide from 70:1 at the Oslo Stock Exchange in Norway to 2500:1 for DAX names at Xetra. AFME supports the introduction of this kind of fees, but at the discretion of the venue and not the dictate of a fixed limit.

- Circuit Breakers: While regulators agree that trading venues should have suitable control mechanisms, AFME further points towards a harmonisation of this kind of mechanism between venues. In response to the "Flash Crash", the SEC approved a pilot for single-stock circuit breaker trading pauses for five minutes based on a five-minute window (SEC, 2012b,a) to complement the market-wide circuit breakers which have not been triggered during the "Flash Crash". On

May 31, 2012, the Commission approved a "limit up-limit down" mechanism to replace the single-stock circuit breaker rules as well revised the market-wide circuit breaker rules (cf. SEC, 2012c).

- Annual Disclosure: As the AFME states, this might result in "a large amount of meaningless information being disclosed to regulators", thus not effective as a preventive action to curb negative effects of HFTs.

- Minimum Resting Time: In the MiFID II proposal, a minimum resting time of 500 milliseconds was proposed, but met strong opposition of practitioners. Negative effects might involve a decrease of activity of actual liquidity supply by HFTs due to the higher exposure posed by longer order lifetimes and additional arbitrage opportunities for aggressive HFTs.

- Continuous Operation Requirement: This point goes in line with previous discussions on trading obligations, specifically in the context of HFT market making activities. However, as AFME correctly stated, formal market makers usually received certain incentives when serving the obligation to provide liquidity for a portion of the trading day.

- Transaction Taxes: These were introduced for example in France as well as an additional HFT tax on entities located in France. Although claiming to target HFT activity with this measure, it affected the whole market and led to deteriorations in some dimensions of market quality (cf. Meyer et al., 2013; Colliard and Hoffmann, 2013; Haferkorn and Zimmermann, 2013). The direct effect of the HFT tax on HFT might also be limited since most HFT firms trading French names would be located outside of France.

While HFT is often viewed as entirely negative, it should be noted that not all behaviors attributable to HFT strategies are detrimental to the market (Credit Suisse, 2012). Thus, despite the variety of possible HFT regulation, the negative effects of manipulative strategies should be targeted more directly, as stated in the Credit Suisse Report, by updating the EU Market Abuse Directive (MAD) to "more accurately reflect newly identified practices like quote stuffing" rather than imposing "new, overly burdensome regulation".

2.2.4 Case Study: HFT and Liquidity

The case study on the HFT contribution to market quality makes use of a subset of the transaction data analyzed in Section 3 and uses quote data from NASDAQ. The data sample consists of trade and quote data of three weeks between 2008 and 2010, specifically September 15-19, 2008, October 05-09, 2009, and February 22-26, 2010. The dataset indicates 26 HFT firms as HFT, while the non-HFT group includes the remaining trading firms. While the non-HFT group includes more than 1000 trading firms on NASDAQ, the results for trading activity are limited to the interpretation of these two groups. The trade data contains identifiers that characterize the liquidity demander and provider of the trade as HFT and non-HFT. The specific trade types are HH, HN, NH, and NN, with HH for example involving HFT as liquidity demander as well as liquidity supplier. The quote data contains best bid and ask prices and sizes quoted by HFT as well as non-HFT. Trade and quote data is on a millisecond basis. The original stock sample of 120 stocks is the result of a random pick to ensure an unbiased sample. Stocks with less than 10 transactions per day and with less than one trade per day that involves HFT within the sample period are deleted.

Table 2.4: Final Sample Constituents and their Market Capitalization

			Stock IDs
	No. of stocks	39	AA AAPL ADBE AGN AMAT AMGN AMZN AXP
	Mean	50,885	BHI BIIB BRCM CB CELG CMCSA COST CSCO
	Std. Dev.	51,660	DELL DIS DOW EBAY ESRX GE GENZ GILD
Mcap 1	Min	11,178	GLW GOOG GPS HON HPQ INTC ISRG KMB
	Max	202,890	KR MMM MOS PFE PG PNC SWN
	No. of stocks	39	AINV AMED ARCC AYI BRE BXS CBT CETV
	Mean	1,878	CKH CNQR COO CPWR CR CRI CSE CSL
	Std. Dev.	314	CTSH ERIE EWBC FCN FL FMER FULT GAS
Mcap 2	Min	1,138	ISIL JKHY LANC LECO LPNT LSTR MANT MELI
	Max	2,397	NSR NUS PNY PTP ROC SF SFG
	No. of stocks	39	ABD ANGO APOG AZZ BAS BW BZ CBEY
	Mean	445	CBZ CCO CDR CPSI CRVL CTRN DCOM DK
	Std. Dev.	92	EBF FFIC FPO FRED IMGN IPAR KNOL MAKO
Mcap 3	Min	309	MDCO MFB MIG MOD MRTN MXWL NC NXTM
	Max	775	PBH PPD RIGL ROCK ROG RVI SJW
	No. of stocks	117	
	Mean	18,154.89	
	Std. Dev.	38,195.84	
Total	Min	309.1	
	Max	202,890.21	

The final data sample consists of 117 Russell 3000 stocks. Table 2.4 presents sample constituents and their statistics. The values of market capitalization (Mcap) are in $ million. The sample contains large companies with a high market capitalization, e.g. General Electric Company and Apple Inc., as well as smaller companies with a low market capitalization, e.g. Acco Brands Corp. and Maxwell Technologies Inc. The sample is ranked by their average market capitalization (Mcap) over the entire sample. It is further categorized into three market capitalization groups: Mcap 1 (39 stocks with the highest Mcap), Mcap 2 (39 stocks with medium Mcap), and Mcap 3 (39 stocks with low Mcap).

NASDAQ itself is the world's largest exchange company and has over 20% of the market share in listed U.S. equity. It is a fully electronic market, with trading hours from 9:30 a.m. to 16:00 p.m. There are call auctions, called "crosses", throughout the day: an opening cross at 9:30 a.m., a closing cross at 4:00 p.m., as well as three intraday crosses. This study focuses only on continuous trading periods, thus the first and last fifteen minutes of the trading period are deleted in order to avoid data errors from opening and closing procedures.

The descriptives give insight about the contribution of HFT on market quality. The contribution of HFT to market quality as compared to non-HFT is evaluated, grouped by the categories market activity and liquidity. Robust Thompson clustered standard errors are applied to test for significance of the differences between HFT and non-HFT measures (c.f. Thompson, 2011).

Table 2.5 presents the contribution of HFT to market activity. Measures of trading activity and quoting activity are distinguished. H_{init} and N_{init} indicate that the trade initiator is a HFT and non-HFT respectively, while H_{pass} and N_{pass} indicate whether the passive order was from a HFT or a non-HFT. The difference between H_{init} and N_{init} as well as H_{pass} and N_{pass} is shown in the column Diff with the t-statistic in parentheses. Turnover is the average daily trading volume in $ million, Trade Count the average number of trades per day, Trade Size the average number of shares per trade, and Quote Frequency the total number of price and volume updates per day. Quote Frequency is grouped by the initiator of the quote update, i.e. HFT (H_{init}) or non-HFT (N_{init}). ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

HFT initiate a smaller portion of the trades, in terms of turnover and trade count, and that they use smaller initiating orders. Non-HFT make up around 55% of the total turnover in the sample period and they also initiate 54% of the trades. Although this result is counterintuitive, I have previously pointed out limitations relating to the data. The comparison of the group HFT consisting of 26 HFT firms and the remaining firms demonstrates that turnover and trade count per firm is actually higher for HFTs.

Therefore these results on trading activity provide an additional reference point to interpret the following results. As expected from the previous discussions of trade characteristics and definition of HFT, trades initiated by HFT involve a smaller trade size measured in number of shares. The right part of the table presents results for trading activity grouped by the passive side of a trade. Although HFT provide less liquidity in terms of turnover, they provide liquidity more often than non-HFT, as shown in the results for trade count. The smaller turnover can be related to the smaller trade size, from which one can infer that HFT trade smaller order sizes when they demand and supply liquidity.

The quoting activity is measured by the number of price and volume updates per day. The number of quote updates initiated by HFT is threefold the number of quote updates initiated by non-HFT. From the results for trading activity and quoting activity, one can infer a significant amount of market making strategies by HFTs since HFTs supply a similar amount of liquidity in terms of trade count, but provide less liquidity in terms of turnover. This is accompanied by a smaller trade size and a high quoting activity.

In order to analyze how HFT influence the total liquidity provision and liquidity demand of the market, quote- and trade-based measures are separated in Table 2.6. Quote-based measures are grouped by HFT ($NHFT$), which denotes the case when HFT (non-HFT) provide liquidity on both sides of the spread, i.e. supply liquidity at the best bid and ask price. For trade-based measures, H_{init} and N_{init} indicate that the trade initiator is a HFT and non-HFT respectively, while H_{pass} and N_{pass} indicate whether the passive order was from a HFT or a non-HFT. Diff is the difference between H_{init} and N_{init}, as well as H_{pass} and N_{pass} respectively. ***, **, and * denote

Table 2.5: Trading and Quoting Activity of HFTs

This table presents the contribution of HFT to trading and quoting activity. H_{init} and N_{init} indicate that the trade initiator is a HFT and non-HFT respectively, while H_{pass} and N_{pass} indicate whether the passive order was from a HFT or a non-HFT. The difference between H_{init} and N_{init} as well as H_{pass} and N_{pass} is shown in the column $Diff$ with the t-statistic in parentheses. Turnover is the average daily trading volume in $ million, Trade Count the average number of trades per day, Trade Size the average number of shares per trade, and Quote Frequency the total number of price and volume updates per day. Quote Frequency is grouped by the initiator of the quote update, i.e. HFT (H_{init}) or non-HFT (N_{init}). ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Panel A: Trading Activity

	Mean	H_{init}	N_{init}	Diff (t-stat)	H_{pass}	N_{pass}	Diff (t-stat)
Turnover	59.825	27.015	32.841	-5.826** (-2.066)	26.154	33.716	-7.562** (-2.007)
Trade Count	8,336	3,814	4,526	-712*** (-2.333)	4,356	3,987	369 -0.814
Trade Size	128	119	134	-15*** (-7.289)	115	138	-23*** (-9.376)

Panel B: Quoting Activity

	Mean	HFT	$NHFT$
Quote Frequency	84,787	62,461	22,436

significance at the 1%, 5%, and 10% level respectively.

The quoted spread in case HFTs provide liquidity on both sides of the market is significantly higher compared to the case when non-HFT are on both sides of the market, while the depth is significantly lower when HFT are best on both sides of the market. This means that HFT provide liquidity when the market is less liquid, meaning that liquidity is rather expensive since quoted spreads are higher and depth is lower. The trade-based measures are determinants when HFT initiate trades and when they provide liquidity. The spread measures are all significantly lower when HFT initiate a trade, which means that they trade more aggressively when liquidity is cheap. As for the liquidity supply of HFT, there is a confirmation on the observation that HFT supply liquidity when it is expensive. They provide liquidity in case of significantly higher quoted spread at trade and effective spreads as well as lower depth.

2.3 Summary

This chapter discussed the technological and economic aspects of the electronic evolution and the technological innovation HFT. The first section concerning the electronic evolution gives insight into the different technological and economic factors involved in the improvement of market quality.

While HFT is currently undergoing more regulatory inspections, it is still a major driver for technological and economic advances in electronic trading. This is especially shown by the developments of internal market structure, specifically IT system, business structure, and market microstructure. HFT challenges marketplaces to improve and invest in their IT system in order to meet the needs of computer traders. Additionally, these marketplaces also adapt their business structure in order to attract HFT and adjust their market microstructure to make this kind of trading possible and safe. The adaptations of the internal market structure as well the increased HFT activity had different effects on market quality. The empirical results indicate the contribution of HFT and non-HFT to different extents on different measures of market

Table 2.6: HFT Liquidity Provision and Demand

This table presents quote- and trade-based measures liquidity provision and demand measures. Quote-based measures are grouped by HFT ($NHFT$), which denotes the case when HFT (non-HFT) provide liquidity on both sides of the spread, i.e. supply liquidity at the best bid and ask price. For trade-based measures, H_{init} and N_{init} indicate that the trade initiator is a HFT and non-HFT respectively, while H_{pass} and N_{pass} indicate whether the passive order was from a HFT or a non-HFT. Diff is the difference between H_{init} and N_{init}, as well as H_{pass} and N_{pass} respectively. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Panel A: Quote-based Measures					
	Mean	HFT	$NHFT$	Diff	t-statistic
Quoted Spread	13.721	13.954	11.894	2.060***	-3.687
Depth	38,004	40,194	41,760	-1,566***	(-3.883)

Panel B: Trade-based Measures							
	Mean	H_{init}	N_{init}	Diff (t-statistic)	H_{pass}	N_{pass}	Diff (t-statistic)
QSpread	8.762	8.175	8.999	-0.824*** (-4.188)	9.901	8.498	1.403*** (-2.445)
ESpread	6.847	5.774	7.165	-1.391*** (-4.786)	8.07	6.625	1.445*** (-4.638)
RSpread5	-0.665	-1.764	-0.273	-1.492*** (-4.975)	0.728	-0.871	1.599 (-1.197)
RSpread15	-0.769	-1.61	-0.448	-1.162*** (-2.767)	0.968	-1.014	1.982 (-1.019)
Depth	36,804	36,343	37,331	-988* (-1.521)	36,045	37,645	-1,601*** (-5.146)

quality. In general, a significant amount of HFT engages in market making strategies. They provide liquidity when it is expensive and demand liquidity when it is cheap, which is also in line with the results of Hendershott and Riordan (2009) and support the existing results in academic literature that found predominantly positive effects of HFT. It is shown that a majority of HFT apply market making strategies and that only 26 HFT firms make up more than 40% of the total trading volume in the data sample. This result shows the importance of HFT and adds to the concern whether such a large amount of trading volume coming from a small group of traders could pose systemic risk to financial markets.

Chapter 3

HFT and Information Processing

In recent years, the nature of information flow and its role in financial markets have significantly changed. The growing amount and complexity of information accessible have reached the human boundaries of information processing capacity. Thus, more computer algorithms are used in order to process large amounts of data in less time. One specific group of computer trading algorithms are HFTs. Common information processing strategies applied by HFTs are arbitrage and news trading strategies. Statistical arbitrage realizes profits from mispricings between different assets. Index arbitrage, being a subset of statistical arbitrage, focuses on mispricings between an index (such as the S&P 500 or the market volatility index VIX) and its components. In the context of qualitative textual information, recent investments in the area of machine-readable news have made the automation of news information processing and thus computerized trading on this information easier (cf. New York Times, 2010). Recent investments have been made by NASDAQ and Deutsche Börse in 2011 to integrate machine-readable economic news into their line of services offered for trading firms and specifically automated traders (Wall Street Journal, 2011b).

In this chapter, I analyze the use of "hard" futures price information for index arbitrage strategies and the use of "soft" textual news information for news trading strategies by HFTs and non-HFTs and implications for price discovery and trading profits. Petersen (2004) characterizes "hard" information as quantitative and easily processable and storable by computers, while "soft" information is qualitative and harder to interpret by computers. Based on this classification, I focus on the following research questions:

> **Research Question 3a:** *What is the market impact of hard and soft information events?*
>
> **Research Question 3b:** *How do HFT and NHFT process hard and soft information shocks?*
>
> **Research Question 3c:** *What is the value of speed in information processing?*

I have three major findings: Firstly, I show that HFTs dominate non-HFTs in processing hard information. Their reaction to hard information is stronger than the reaction of non-HFTs. Specifically, they react strongly to hard information within 10 seconds and sell out their trading position within 2 minutes. Thereby, they function as "messengers" between the futures and stock market and create a stronger linkage between both markets. Secondly, I demonstrate that speed matters for information processing and for realizing trading gains because of very high realized and fictitious trading profits within the first 10 seconds. Thirdly, I find no evidence for automated news trading by HFTs, but rather a dominance of non-HFTs in processing soft news information. In the context of soft information, speed plays a less important role and the trading profits are comparably lower.

These results suggest a split of the trading world: On one side, the high frequency world is dominated by HFTs which specialize in the processing of hard information within a short amount of time. On the other side, the low-frequency world is still dominated by non-HFTs that have better information processing abilities with respect to soft information and engage in strategies for longer periods than HFTs. I follow the classification of hard and soft information that is suggested in Jovanovic and Menkveld (2012) in a HFT context. A similar dimension of information classification is introduced by Martinez and Roşu (2013) with the level of "news precision".

I confirm the theoretical findings of Martinez and Roşu (2013) and Foucault et al. (2013) on a higher HFT activity and informed variance ratio with increased news precision. I further provide evidence of larger effects in periods of heightened volatility as shown by Foucault et al. (2013): For high volatility periods, short-term HFT net trading in the direction of the information event are even higher than for low volatility periods as well as trading profits, which makes higher speed and trading volume even more important.

Furthermore, I provide further insight into the price discovery process of and the role HFTs play in interlinked markets. The lead-lag relationship between the futures and stock market has been well-documented in finance literature, such as by Hasbrouck (2003) and Theissen (2012). In this context, I show that HFTs strengthen the interlinkage and contribute to a higher efficiency between both markets.

3.1 Related Literature

A major concern of regulatory authorities, such as the U.S. Securities and Exchange Commission (SEC) and the US Commodity Futures Trading Commission (CFTC), is the influence of HFT on market quality and price discovery (cf. the call for comments of the SEC, 2010). This study relates to HFT literature on information and price discovery as well as literature on different categories of information events (hard and soft).

3.1.1 HFT and Price Discovery

Empirical evidence shows that HFT contributes to price discovery and improve price efficiency. Brogaard et al. (2013) use a state space model to decompose the market return time series into a transitory component (i.e. pricing errors) and a permanent component (i.e. permanent price changes). They find a positive relationship of HFT initiated trades with permanent price changes, while HFT passive trades are positively related to pricing errors. They further find an increase in trades initiated by HFTs after macroeconomic news. O'Hara et al. (2011) study the contribution of odd-lot trades[1] to price discovery. They show that odd-lot trades account for 30% of price discovery. Chaboud et al. (2013) find that AT increase price efficiency in FX markets

[1]Odd-lot trades are trades below 100 shares. They are often used by Algorithmic Traders (ATs) and HFTs as a result of slicing large orders into smaller ones in order to hide trading intentions.

by applying triangular arbitrage strategies. I strengthen previous results by showing that HFTs also engage in index arbitrage strategies and thus create an efficient linkage between futures and stock markets.

The results are closely related to the theoretical findings of Martinez and Roşu (2013) and Foucault et al. (2013), and empirical findings of Jovanovic and Menkveld (2012). Martinez and Roşu (2013) show that with increasing news precision, trading volume, and the informed variance ratio increases. Foucault et al. (2013) compare two models based on the model by Kyle (1985): one "fast" model in which the informed trader has a speed advantage in addition to his superior information processing possibilities and one benchmark model without speed advantage. Jovanovic and Menkveld (2012) find a positive relationship between HFT activity and hard information days.

In order to estimate the value of speed, I further study HFT profits after information events. General HFT profits are studied by Menkveld (2013) who analyzes the influence and profitability of a HFT market-maker on Chi-X. Baron et al. (2012) further analyze HFT profitability in the E-mini futures markets and the time-horizon of profitability. In contrast to these studies, I concentrate on trading profits of HFT after information events.

3.1.2 Categories of Information Events

Various types of information events and their effect on financial markets have been analyzed in finance literature, for example earnings announcements, macroeconomic news, and stock-specific news arrivals among others.

The studied information events can be classified into hard and soft information according to Petersen (2004). He characterizes hard information as quantitative and easily processable and storable by computers, such as stock prices and market indices. On the contrary, soft information is qualitative and hard to interpret by computers, e.g. news ticker items, blog posts or even Twitter messages. The distinction between hard and soft information can be ambiguous: Futures returns are quantitative information and can be interpreted relatively easily, while VIX returns, however quantitative, involves a higher uncertainty of interpretation and prediction of subsequent market reactions than of futures shocks.

In the context of machine-readable news, Petersen (2004) mentions the possibility of hardening soft information with the use of algorithms. The automatic transformation of textual information into numbers has made the border between hard and soft information more blurred and offers opportunities to include this information in trading strategies. I argue that although certain sentiment and relevance measures of the news dataset might be included into automated strategies, the interpretation and use of the measures is still ambiguous and thus qualify as soft information.

The classification of hard and soft information is also applied by Jovanovic and Menkveld (2012) and Engelberg (2008). Jovanovic and Menkveld (2012) find a positive relationship between HFT activity and hard information days. Engelberg (2008) extracts a hard and a soft information component of earnings announcements. The hard information component is based on accounting data while the soft component is based on the text of news articles on the earnings announcement.

Literature on soft information uses different information types, such as a *Wall Street Journal* column (Tetlock, 2007), newswire messages (Tetlock, 2010), and Internet stock messages boards (Antweiler and Frank, 2004). Current research in computer science is further evolving to use social media, such as Twitter messages, to predict box-office revenues for movies (Asur, 2010) and market returns (Bollen et al., 2011). In this study, I focus on Reuters news ticker data which is described in the following section.

3.2 Data and Sample Descriptives

There are few datasets available that directly identify AT and HFT. Datasets used in research often use proxies for HFT and AT (such as Hendershott et al., 2011; Hasbrouck and Saar, 2013). Only recently, data with specific AT and HFT identifiers has become available. Hendershott and Riordan (2009) use data from Deutsche Börse in Germany. The same dataset as in this study is also used for research by Brogaard et al. (2013) and O'Hara et al. (2011).

I match the high frequency information datasets with a proprietary HFT dataset provided by NASDAQ.[2] Trade data is tick-by-tick data time-stamped to milliseconds and identifies the liquidity demander and liquidity supplier of a trade as a HFT or non-HFT. It covers the years 2008 and 2009. The information datasets include abnormally high and low S&P 500 futures returns and VIX returns as hard information shocks and Reuters news ticker data as soft information shocks.

3.2.1 Sample Descriptives

I restrict my data sample to 40 stocks listed in the S&P 500 index which provide a sufficiently high number of high frequency trades and news items. Descriptives of the data sample are shown in Table 3.1.

The trading volume in “Traded Shares” shows that the NASDAQ trading volume in this sample represents around 30% of the total volume of sample stocks. The minimum number of HF trades per day is 125; thus the chosen sample provides sufficient observations for analysis. The final stock sample consists of 40 stocks listed in the S&P 500 index: 20 listed on NYSE and 20 listed on NASDAQ. The complete list of sample stocks and relative portion of HFT can be found in Appendix A.1, Table A.1. Sample stocks are highly capitalized with an average of $47 billion. I distinguish between the HFT group demanding liquidity (HFT_{init}) and supplying liquidity (HFT_{pass}) as well as the corresponding non-HFT group demanding liquidity ($NHFT_{init}$) and supplying liquidity ($NHFT_{pass}$). Only continuous trading is considered in order to measure the direct intra-day reaction after an information event. The first and last five minutes of each trading day are omitted in order to leave out trading on overnight information and biases associated with market opening and closing. Thus, the data spans the time interval from 9:35 a.m. to 3:55 p.m.

[2] I thank Frank Hathaway and Jeff Smith for providing access to the data as well as Terrence Hendershott and Ryan Riordan for compiling the dataset. For further information on the dataset see Brogaard et al. (2013).

Table 3.1: Summary Descriptives

This table provides descriptives of the final sample of 40 stocks and information events for the years 2008 and 2009. Panel A depicts the descriptives of the stock sample based on averages per stock-day. *MarketCap* denotes the average market capitalization of the stocks and *Price* the average stock price. *TradedShares* is the average total number of shares traded, *TradeVolume* is the traded volume. HFT_{init} and HFT_{pass} are net trading (buyer-initiated minus seller-initiated trade volume) of trades that were initiated by HFT and where HFT were on the passive side respectively. Trade variables are aggregated to ten seconds intervals and standardized by mean and standard deviation of the respective stock-day. *Return* is the average 10 second-logreturn of the stock price. *VIX* is the average daily price for the Chicago Board Options Exchange (CBOE) Volatility Index and *Future* the average daily price for the S&P 500 future. Panel B depicts descriptives of the chosen information time series, i.e. S&P 500 future returns and VIX returns, and Panel C the descriptives of the information events. *News* is the average number of news items per stock-day. Future and VIX shocks are return above the 99% and below the 1% percentile.

Panel A: Sample Descriptives

Variable	**Source**	**Unit**	**Mean**	**Std**
Market Cap	Compustat	$ 1 million	47,172	52,294
Price	Compustat	$	55.80	76.83
Traded Shares	Compustat	# million shares	16.648	24.352
Traded Shares	NASDAQ	# million shares	4.843	6.846
Traded Volume	NASDAQ	$ 1000	80	251
HFT_{init}	NASDAQ	$	29	98,701
HFT_{pass}	NASDAQ	$	-1	98,359
Return	NBBO	1 bps	0.001	0.989
Future	SIRCA		1,087	209
VIX	SIRCA		32	13

Panel B: Information Descriptives

Information	**Mean**	**Std**	**1% Perc**	**99% Perc**
Future Returns	0.003	5.055	-10.914	11.050
VIX Returns	-0.022	17.488	-24.233	23.841

Panel C: Information Events

Information	**# Events**	**# Positive**	**#Negative**
News	3,238	1,560	1,678
Future Return Shocks	24,429	12,210	12,219
VIX Return Shocks	23,934	11,967	11,967

3.2.2 Hard and Soft Information

Information events are manifold and can be categorized based on a number of dimensions. Following Petersen (2004), I distinguish between "hard" and "soft" information events. I present three proxies for information events, futures return shocks, news events, and VIX return shocks and discuss their characteristics in more detail. They are derived from recent literature. I argue that all three information datasets fulfill the requirement for exogenous shocks in order to run a de facto impulse response analysis in Section 3.3.2.

For hard information shocks, I choose S&P 500 futures return shocks and volatility index (VIX) price return shocks. S&P 500 futures prices and VIX prices are collected on a tick by tick basis from Thomson Reuters Tick History.[3] Jovanovic and Menkveld (2012) propose the R squared from a capital asset pricing model (CAPM) based on stock returns and market futures returns as a proxy for the relevance of hard information. Hence, I consider market futures returns as a proxy for hard information. I exclude the first and last 5 minutes of the trading day and determine the 1% and 99% percentiles of S&P 500 futures 10 second returns over the whole observation period. Returns above the 99% and below the 1% level are considered as futures return shocks.

I also include VIX prices in my analyses. The VIX is published by the Chicago Board Options Exchange (CBOE) and is constructed from the implied near-term volatility of S&P 500 stock index option prices.[4] Similar to futures returns, VIX price returns can be easily processed by HFTs and therefore qualify as hard information. However, the information content of a futures shock as compared to a VIX price shocks is of a different nature with different implications for HFTs and non-HFTs. As suggested by Foucault et al. (2013), volatility increases are followed by an increase of HFT flow trading. I apply the same methodology as the analysis of futures returns and analyze the relationship between abnormally high and low VIX returns and subsequent HFT and non-HFT activity.

[3] I thank SIRCA for providing access to the Thomson Reuters DataScope Tick History.

[4] VIX is widely considered as a measure for investor sentiment and market volatility, `http://www.cboe.com/micro/VIX/vixintro.aspx`.

News data serves as a proxy for soft information. The news dataset is provided by Thomson Reuters and contains firm-specific newswire items time-stamped to milliseconds. An exemplary news item is shown in Figure 3.1. Each news item includes a time stamp, a stock ticker symbol (BCAST_REF), a relevance indicator, a sentiment indicator, probabilities of the news item having a positive, neutral, or negative tone (SENT_POS, SENT_NEUT, SENT_NEG), a linked count (LNKD_CNT1) that represents the count of linked articles in a particular time period, the PNAC (Primary News Access Code, a semi-unique story identifier), as well as topic codes among others. The dataset allows a differentiation of news items based on the indicators *Sentiment*, and *Relevance*. *Sentiment* can be either negative (-1), neutral (0), or positive (+1) depending on the news item. *Relevance* is a real number on the interval [0,1]. I only consider positive and negative news items during continuous trading hours. Gross-Klussmann and Hautsch (2011) find a significant market reaction only to relevant news items. Thus, I concentrate only on news items that are relevant to the specific stock ($Relevance = 1$). Furthermore, news items with identical PNAC within the same day as well as are deleted so only new information is considered.

The news dataset is professionally processed by algorithms of the Reuters News Sentiment Engine (RNSE) which is used by practitioners and academics.

The descriptives of the chosen hard and soft information events are presented in Table 3.1, Panel B and Panel C.

3.3 Results

This section presents the correlation results as well as results on the market impact of hard and soft information events, the impact on HFT and NHFT net trading, contribution to price discovery, and HFT profits.

3.3.1 Correlation Results

Correlation results on trading variables and information event dummies give us first indications of trading behavior after information events. Trade variables in Panel A

TIMESTAMP	03Jan08:21:08:59.500
BCAST_REF	GOOG.O
ITEM_ID	2008-01-03_21.08.59.nWNAS5601.A1.3663f3ab
RELEVANCE	1
SENTIMENT	1
SENT_POS	0.852683
SENT_NEUT	0.117423
SENT_NEG	0.0298942
LNKD_CNT1	0
...	
BCAST_TEXT	THOMSON INTEGRATES THE POWER OF GOOGLE LOCAL SEARCH INTO NEW LINE OF DEVICES
DSPLY_NAME	1
PNAC	nWNAS5601
...	
TOPIC_CODE	ELI CELE CYCP CYCS HBHG APL ELC EUROPE FR WEU DPR BUS US ITSE SWIT TECH LEN RTRS
CO_IDS	TMS.PA GOOG.O
LANG_IND	EN

Figure 3.1: Exemplary News Item

are net trading volume, i.e. buyer-initiated minus seller-initiated volume to accurately measure the information flow of different trader groups (e.g. Chaboud et al., 2013; Tookes, 2008). In Panel B, I analyze absolute trading volume and illiquidity after information events. Return and trade variables are standardized by the mean and standard deviation of the respective stock-day which makes results comparable across firms. Results are presented in Table 3.2.

Table 3.2: Correlation of Information Shocks, Net Trading and Trading Volume

This table presents the Pearson correlations of return and trade variables and lagged information variables. In Panel A, trade variables are net trading (buy minus sell volume) aggregated to ten seconds intervals and standardized by mean and standard deviation. HFT_{init} denotes net trading of HFT demanding liquidity, HFT_{pass} denotes HFT supplying liquidity, NHFT variables correspond ($NHFT_{init}$, $NHFT_{pass}$). fut is the S&P 500 future 10 second return, vix is the VIX return. *news* is the sentiment of a news event (-1, 0, or 1). The indices 1, 6 and 12 denote the lagged variables after 10, 60 and 120 seconds. In Panel B, trade variables are absolute trading volume (buy plus sell volume) and $Qspread$ denotes the quoted spread. fut, vix, and *news* are dummies for information events in a time interval (equals 1 if information shock occurs, 0 otherwise). Correlation results are reported in %, aggregated per stock-day and tested using double clustered standard errors on stock and trading day. Significant results below the 5% level are bold.

	Panel A: Net Trading											
	fut	**fut1**	**fut6**	**fut12**	**vix**	**vix1**	**vix6**	**vix12**	**news**	**news1**	**news6**	**news12**
HFT_{init}	**8.97**	**-1.35**	**-0.89**	**-0.24**	**0.52**	**0.94**	**0.38**	**0.22**	0.09	0.06	0.08	-0.07
HFT_{pass}	**-3.39**	**-0.36**	**-0.27**	**-0.36**	**0.36**	**0.37**	**0.33**	**0.23**	**-0.17**	**-0.19**	-0.06	-0.07
$NHFT_{init}$	**7.43**	**3.55**	**0.99**	**0.57**	**-2.28**	**-1.58**	**-0.67**	**-0.35**	**0.16**	0.15	0.09	0.05
HFT_{pass}	**-11.09**	**-2.07**	**-0.15**	**-0.18**	**1.48**	**0.60**	**0.19**	0.06	-0.10	-0.11	-0.10	0.02
fut	100	**4.35**	**-0.69**	-0.08	**-9.15**	**-2.10**	0.00	0.13	0.07	0.05	0.05	0.02
$fut1$		100	**-0.44**	**-0.38**	**-17.97**	**-9.37**	0.20	0.08	-0.05	0.09	-0.05	-0.01
$fut6$			100	**-0.68**	**-1.50**	**-2.08**	**-9.16**	-0.01	0.05	0.00	0.08	0.03
$fut12$				100	**-0.59**	**-0.61**	**-1.45**	**-9.21**	0.03	0.06	0.05	**0.10**
vix					100	**-1.42**	0.40	**0.37**	-0.08	-0.09	0.08	0.04
$vix1$						100	0.25	0.22	0.06	-0.07	-0.04	**0.08**
$vix6$							100	0.38	**-0.09**	0.00	-0.08	0.07
$vix12$								100	-0.06	-0.03	**-0.09**	-0.08

...continued from Table 3.2

	Panel B: Absolute Trading											
	fut	**fut1**	**fut6**	**fut12**	**vix**	**vix1**	**vix6**	**vix12**	**news**	**news1**	**news6**	**news12**
$AbsHFT_{init}$	**5.71**	**3.47**	**2.25**	**1.90**	**2.90**	**2.36**	**1.80**	**1.63**	**0.34**	**0.49**	**0.24**	**0.27**
$AbsHFT_{pass}$	**5.39**	**3.55**	**2.22**	**1.88**	**3.03**	**2.48**	**1.81**	**1.63**	**0.41**	**0.62**	**0.36**	**0.30**
$AbsNHFT_{init}$	**4.25**	**2.47**	**1.47**	**1.20**	**2.20**	**1.72**	**1.25**	**1.14**	**0.39**	**0.51**	**0.34**	**0.30**
$AbsNHFT_{pass}$	**4.71**	**2.57**	**1.60**	**1.28**	**2.24**	**1.74**	**1.31**	**1.19**	**0.35**	**0.46**	**0.29**	**0.29**
$Qspread$	**0.69**	**0.96**	**0.93**	**0.85**	**0.54**	**0.68**	**0.56**	**0.52**	0.06	**0.20**	0.07	0.11

The results in Panel A show positive contemporaneous correlations of HFT initiated volume (HFT_{init}) and non-HFT initiated volume ($NHFT_{init}$) with futures shocks and negative correlations with the corresponding passive trade variables (HFT_{pass} and $NHFT_{pass}$). VIX returns are positively related to HFT_{init} and HFT_{pass} for all lags and negatively to initiating non-HFT volume. News sentiment has the highest positive relationship with $NHFT_{init}$. In order to rule out interrelationships between the information events, I also compute correlations of futures and VIX returns and news sentiment. Correlations with news sentiment are negative and low, with the maximum correlation being 0.16% for both futures and VIX and the minimum being -0.19%. In conclusion, I find low correlations between the chosen information events and thus low interrelationships between them.

In Panel B, I present results for absolute trading variables. According to findings by Martinez and Roşu (2013), trading volume and illiquidity increase with news precision. Equating news precision with the hardness of information, I can confirm these findings: I see a higher effect on absolute trading volume and on illiquidity[5] after hard futures shocks and a lower effect after soft news shocks.

3.3.2 Impact of Information Events on Returns and Net Trading

In order to answer the question what type of impact information events have on stock returns and trading behavior, I implement a VARX model based on models of Hasbrouck (1991a) and Chaboud et al. (2013). The VARX model includes three time series: one for stock returns, one for HFT order flow, and one for non-HFT order flow. I control for k lags of stock return, HFT order flow, and non-HFT order flow. The relevant lags after an information shock are denoted by W. The coefficients of interest are $\phi^r_{i,w}$, $\phi^h_{i,w}$ and $\phi^n_{i,w}$ which represent stock return as well as HFT and non-HFT net trading after exogenous information shocks. The subscript i denotes the stock, w denotes lags after an information event.

The VARX model is implemented as follows:

[5]The quoted spread is computed as $Qspread_{i,t} = (AskPrice_{i,t} - BidPrice_{i,t}) / Mid_{i,t}$ for stock i and time t. $Qspread$ is a measure for execution costs of a trade and thus for market illiquidity.

$$
\begin{aligned}
V_{i,t}^{h} &= \alpha_i^h + \sum_{j=1}^{k} \beta_{i,j}^{h} V_{i,t-j}^{h} + \sum_{j=0}^{k} \gamma_{i,j}^{h} V_{i,t-j}^{n} + \sum_{j=0}^{k} \delta_{i,j}^{h} r_{i,t-j} + \sum_{w=0}^{W} \phi_{i,w}^{h} D_{i,w} + \epsilon_{i,t}^{h} \\
V_{i,t}^{n} &= \alpha_i^n + \sum_{j=0}^{k} \beta_{i,j}^{n} V_{i,t-j}^{h} + \sum_{j=1}^{k} \gamma_{i,j}^{n} V_{i,t-j}^{n} + \sum_{j=0}^{k} \delta_{i,j}^{n} r_{i,t-j} + \sum_{w=0}^{W} \phi_{i,w}^{n} D_{i,w} + \epsilon_{i,t}^{n} \\
r_{i,t} &= \alpha_i^r + \sum_{j=0}^{k} \beta_{i,j}^{r} V_{i,t-j}^{h} + \sum_{j=0}^{k} \gamma_{i,j}^{r} V_{i,t-j}^{n} + \sum_{j=1}^{k} \delta_{i,j}^{r} r_{i,t-j} + \sum_{w=0}^{W} \phi_{i,w}^{r,w} D_{i,w} + \epsilon_{i,t}^{r}
\end{aligned} \tag{3.1}
$$

where t denotes the respective 10s interval. $V_{i,t}$ is the signed net order flow (buyer-initiated volume minus seller-initiated volume) of HFT (superscript h) and non-HFT (superscript n) respectively, standardized by mean and standard deviation of the respective stock-day. The model is applied to HFT and non-HFT initiated net order flow (HFT_{init}, $NHFT_{init}$) as well as passive net order flow (HFT_{pass}, $NHFT_{pass}$). For the VARX model, I choose lag length $k = 12$ and $W = 12$, i.e. 2 minutes, in order to gain a comprehensive insight into short and long run behavior for HFTs. $r_{i,t}$ is the standardized return. The coefficients are β_i, γ_i, and δ_i, where superscripts h, n, and r denote HFT, non-HFT, and return respectively. α_i are intercepts and $\epsilon_{i,t}$ error terms. $D_{i,w}$ is a dummy variable and equals one if a positive information shock occurs, -1 if a negative information shock occurs in t or less than W 10s intervals before t, and 0 otherwise.

Results are reported for the contemporaneous impact in the short run within 10 seconds (SR; $\phi_{i,0}^r$, $\phi_{i,0}^h$ and $\phi_{i,0}^n$), the aggregated impact in the long run within 2 minutes (LR; $\sum_{w=0}^{12} \phi_{i,w}^r$, $\sum_{w=0}^{12} \phi_{i,w}^h$ and $\sum_{w=0}^{12} \phi_{i,w}^n$) and the difference, i.e. the long run impact minus the short run reaction between 10 seconds and 2 minutes ($LR - SR$; $\sum_{w=1}^{12} \phi_{i,w}^r$, $\sum_{w=1}^{12} \phi_{i,w}^h$ and $\sum_{w=1}^{12} \phi_{i,w}^n$). In order to gain more insight into the high-frequency domain of hard information processing, I run the model on a 1 second basis with k=10 lags (i.e. 10 seconds) and W=30 lags. The model in Equation (3.1) is estimated as a dynamic simultaneous equation model using two-step least squares. The model is applied to all three information events.

Impact on Stock Returns

Firstly, I characterize the chosen information events with respect to their impact on stock returns. The model in Equation (3.1) is applied to the sum of HFT initiated and passive net order flow ($HFT_{all} = HFT_{init} + HFT_{pass}$) as well as non-HFT order flow ($NHFT_{all} = NHFT_{init} + NHFT_{pass}$).[6] Table 3.3 presents the aggregated coefficients of the VARX model for stock returns of the sample from 2008-2009.

From the results in 3.3, I can infer that the impact of futures shocks on stock returns is highest in the short run, while the impact of news events is increasing in the long run. VIX shocks do lead to a slight decrease in stock returns which also goes along with the negative correlation of VIX returns and futures returns.

Figure 3.2 gives more insight into the high-frequency impact on stock returns, with the highest impact during the first 5 seconds. Thus, hard futures shocks seem to have a high impact on stock returns in the short run while the impact of news events is higher in the long run.

[6]Applying the model only to initiating (HFT_{init} and $NHFT_{init}$) net order flow or passive net order flow (HFT_{pass} and $NHFT_{pass}$) does not yield qualitatively different results.

Table 3.3: Impact of Information Shocks on Stock Returns
This table presents coefficients of stock returns after an information shock. A VARX model is implemented with the dependent variables as the respective trading variables. The independent variables are lagged and contemporaneous HFT and non-HFT order flow and returns. All variables are aggregated into ten second intervals and standardized using mean and standard deviation for each stock and each trading day. The table reports aggregated impact on stock return r. SR denotes the contemporaneous impact in the short run, LR denotes the aggregated impact for the following 12 ten second intervals, i.e. 2 minutes after the information shock, $LR - SR$ denotes the long-run impact minus the short-run impact. Variables are aggregated per stock-day and tested using robust standard errors clustered by stock and trading day (cf. Thompson, 2011). T-statistics are in parentheses. ***, **, and * denotes significance at the 1%, 5%, and 10% level respectively.

	Futures Shocks	*VIX Shocks*	*News Events*
SR	0.556***	0.000	-0.002
(t-stat)	(13.99)	(0.03)	(-0.07)
LR	0.573***	-0.049*	0.198*
(t-stat)	(6.53)	(-1.85)	(1.72)
LR-SR	0.017	-0.049*	0.201*
(t-stat)	(0.24)	(-1.94)	(1.90)

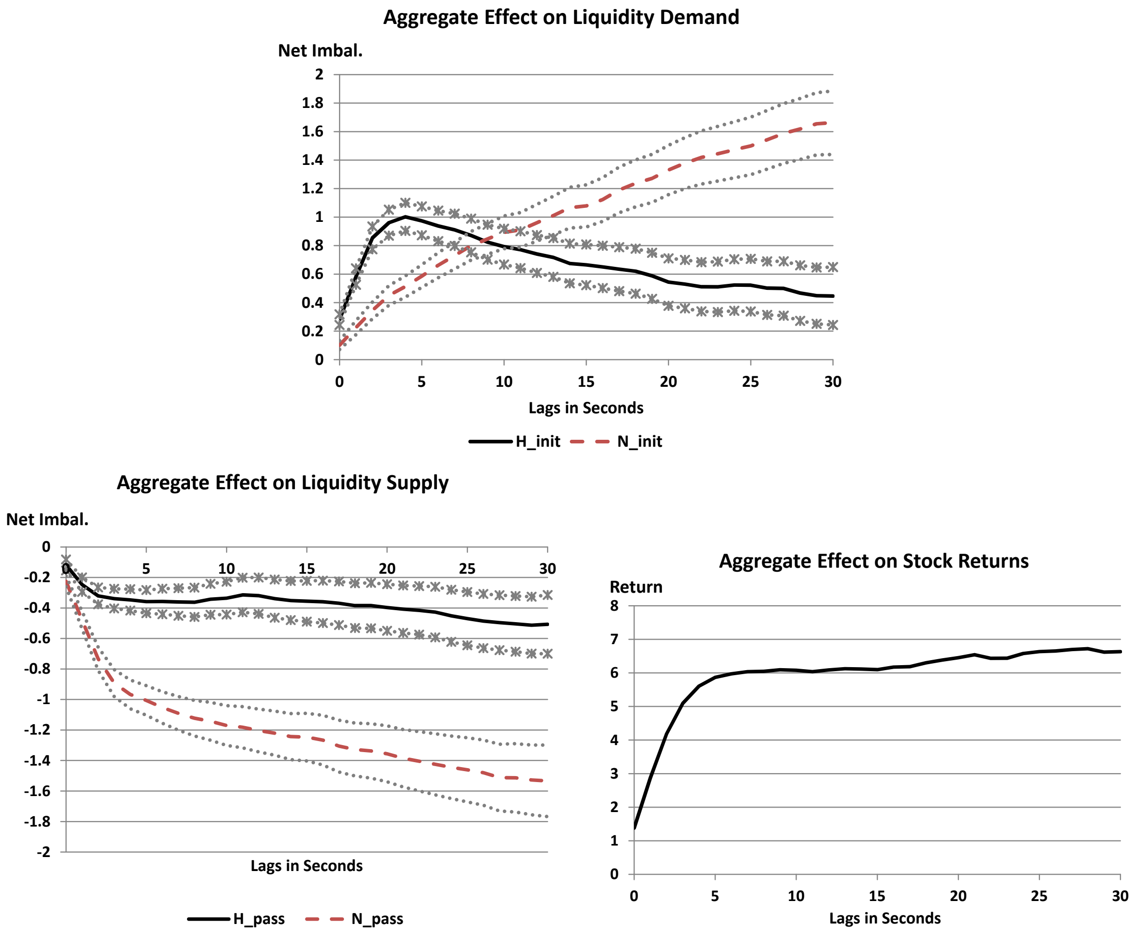


Figure 3.2: Impact of Hard Information Shocks - 1 Second Analysis
This figure shows a plot of initiating and passive HFT aggregate net trading H_{init} (black solid line) and non-HFT net trading N_{pass} (red dashed line) as well as returns after information events. All trade and return variables are standardized by mean and standard deviation. The x-axis denote the lags of the corresponding information events in seconds. The dotted lines with stars represent the 95% confidence intervals for H_{init} and H_{pass} respectively, the dotted lines without stars the 95% confidence intervals for N_{init} and N_{pass}.

Impact on Net Trading

I am further interested in the trade reaction in the short and long run. Table 3.4 presents the aggregated coefficients of the VARX model for S&P 500 futures return shocks in Panel A, VIX shocks in Panel B, and news events in Panel C of the sample from 2008-2009. Results for initiated trades of HFTs (HFT_{init}) and non-HFTs ($NHFT_{init}$) and their difference ($Diff$) are on the left hand side and results for passive trades on the right hand side. Figure 3.3 depicts the results for initiated net trading after information events graphically, Figure 3.4 depicts the results for passive net trading after information events.

After the occurrence of an information event, I argue that net trading in the direction of this information event can be interpreted as informed trading activity based on the event. Thus, the rationale of interpretation is positive net trading, i.e. more buy than sell orders, after positive information shocks and negative net trading after negative information shocks. The information shocks are represented by directed dummies $D_{i,w}$ as mentioned above, i.e. -1 for negative shocks and +1 for positive shocks. Thus, the coefficients of the model can be interpreted as the impact of a directed information shock on net trading in the same direction.

As shown in Panel A, initiating HFTs show a significant and positive reaction to futures shocks in the short run (0.240). In case of a futures price increase, initiating HFTs thus demonstrate a 24% of the 10 second standard deviation higher amount of buy volume than sell volume as compared to the average net trading. Initiating HFTs invert their trading behavior within two minutes in the long run (-0.249 in LR-SR), representing a complete liquidation of the trading position acquired within the first 10 seconds. The analysis on a 1 second level gives more insight into the high frequency impact and reveals that the highest impact on HFT net trading is during the first 5 seconds after the information event. Differently, non-HFTs exhibit a consistently positive reaction to the information shock (0.179 in the short run and 0.350 in the long run). As a consequence, the difference between HFTs and non-HFTs initiated trading, $Diff$, results in a positive coefficient in the short run (0.061), but a negative coefficient in the long run (-0.420 in LR-SR). The different reaction of HFTs and non-

Table 3.4: Impact of Information Shocks on Net Trading

This table presents coefficients of HFT and non-HFT net trading after an information shock. A VARX model is implemented with the dependent variables as the respective trading variables. The independent variables are lagged and contemporaneous HFT and non-HFT order flow and returns. All variables are aggregated into ten second intervals and standardized using mean and standard deviation for each stock and each trading day. Panel A reports aggregated impact on initiating and passive net trading for HFT (HFT_{init}, HFT_{pass}) and non-HFT ($NHFT_{init}$, $NHFT_{pass}$) as well as their respective difference ($Diff$). Panel B reports result for VIX shocks and Panel C for news events. SR denotes the contemporaneous impact in the short run, LR denotes the aggregated impact for the following 12 ten second intervals, i.e. 2 minutes after the information shock, $LR - SR$ denotes the long-run impact minus the short-run impact. Variables are aggregated per stock-day and tested using robust standard errors clustered by stock and trading day (cf. Thompson, 2011). T-statistics are in parentheses. ***, **, and * denotes significance at the 1%, 5%, and 10% level respectively.

Panel A: Futures Shocks

	Initiating Order Flow			*Passive Order Flow*		
	HFT_{init}	$NHFT_{init}$	$Diff$	HFT_{pass}	$NHFT_{pass}$	$Diff$
SR	0.240***	0.179***	0.061**	-0.102***	-0.272***	0.170***
(t-stat)	(9.06)	(13.40)	(2.51)	(-6.75)	(-12.93)	(10.89)
LR-SR	-0.249***	0.171***	-0.420***	-0.160***	0.083	-0.243***
(t-stat)	(-6.71)	(2.69)	(-5.57)	(-5.37)	(1.64)	(-4.77)

Panel B: VIX Shocks

	Initiating Order Flow			*Passive Order Flow*		
	HFT_{init}	$NHFT_{init}$	$Diff$	HFT_{pass}	$NHFT_{pass}$	$Diff$
SR	0.029***	-0.021***	0.049***	0.017***	-0.010**	0.027***
(t-stat)	(4.85)	(-5.79)	(9.75)	(4.43)	(-2.01)	(6.25)
LR-SR	0.049***	-0.146***	0.195***	0.202***	-0.007	0.208***
(t-stat)	(2.59)	(-7.21)	(6.71)	(11.90)	(-0.36)	(9.90)

Panel C: News Shocks

	Initiating Order Flow			*Passive Order Flow*		
	HFT_{init}	$NHFT_{init}$	$Diff$	HFT_{pass}	$NHFT_{pass}$	$Diff$
SR	0.027	0.080**	-0.053	-0.065*	-0.053**	-0.012
(t-stat)	(1.04)	(2.45)	(-1.50)	(-1.94)	(-1.98)	(-0.40)
LR-SR	0.114	0.328**	-0.213	-0.352***	-0.280*	-0.071
(t-stat)	(1.20)	(2.17)	(-1.49)	(-4.22)	(-1.81)	(-0.47)

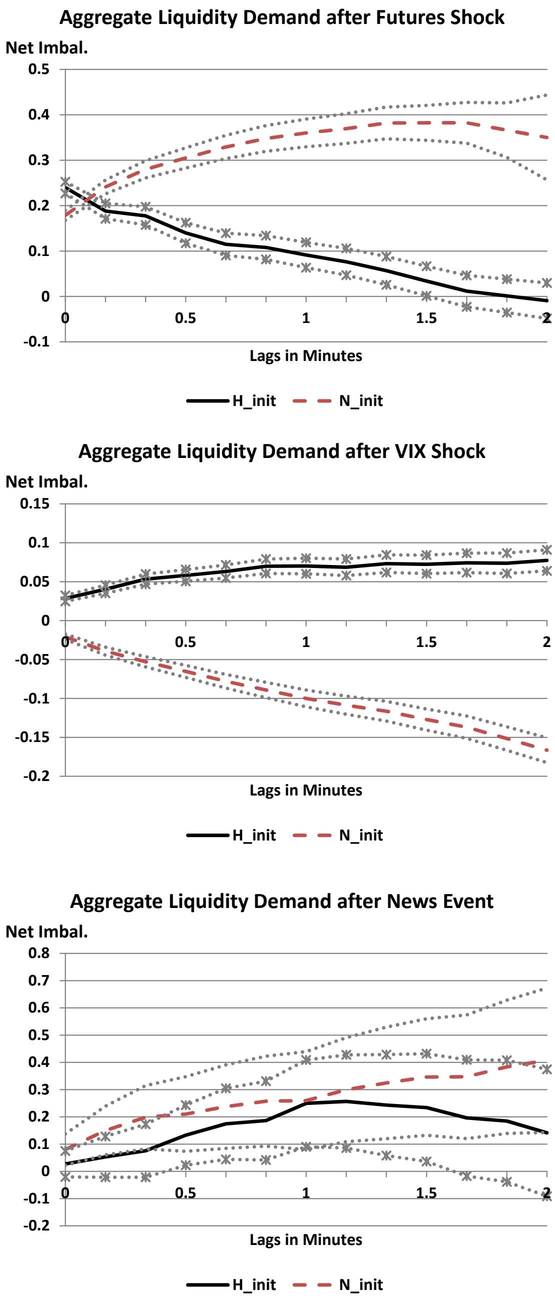


Figure 3.3: Initiated Net Trading after Information Events
This figure shows a plot of initiating HFT aggregate net trading H_{init} (black solid line) and non-HFT net trading N_{init} (red dashed line) after information events. All trade variables are standardized by mean and standard deviation. The x-axis denote the lags of the corresponding information events in minutes. The dotted lines with stars represent the 95% confidence intervals for H_{init}, the dotted lines without stars the 95% confidence intervals for N_{init}.

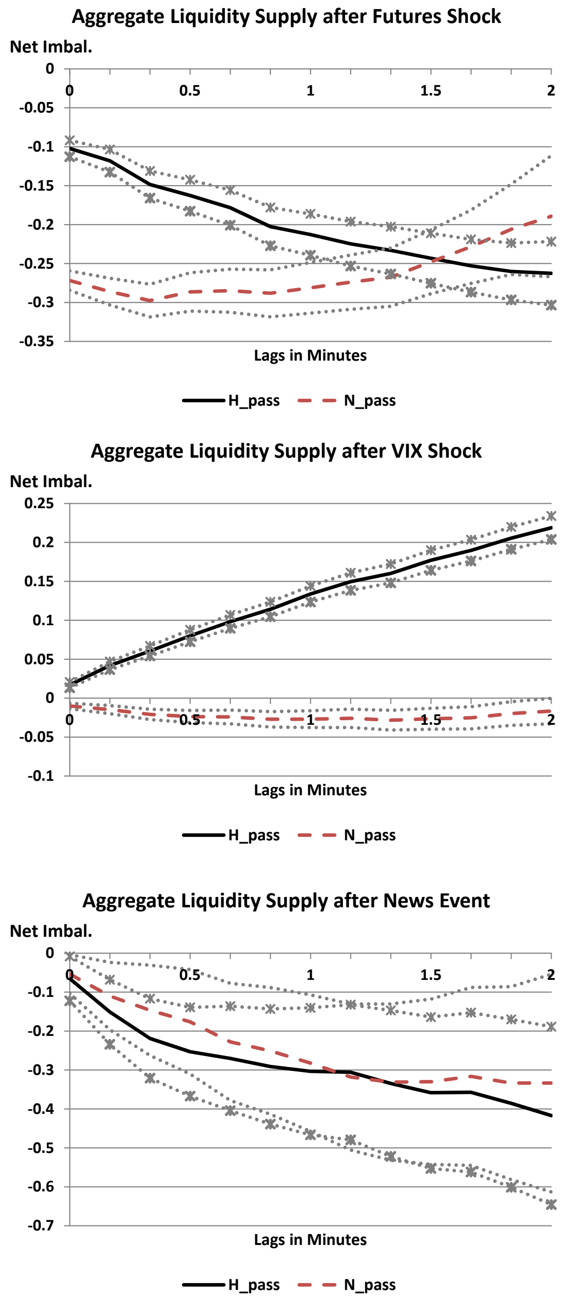


Figure 3.4: Passive Net Trading after Information Events
This figure shows a plot of passive HFT aggregate net trading H_{pass} (black solid line) and non-HFT net trading N_{pass} (red dashed line) after information events. All trade variables are standardized by mean and standard deviation. The x-axis denote the lags of the corresponding information events in minutes. The dotted lines with stars represent the 95% confidence intervals for H_{pass}, the dotted lines without stars the 95% confidence intervals for N_{pass}.

HFTs can be interpreted that HFTs are able to react faster to hard information shocks, such as futures return shocks. In the long run, HFTs trade in the opposite direction of the futures shock. This points to a reduction of their trading positions and thus a realization of their short-term profits.

Panel B presents the aggregated coefficients of the VARX model in Equation (3.1) for VIX return shocks. I provide insight into the trading behavior of HFTs for periods of extremely high volatility events, measured by VIX return shocks above the 99% level and below the 1% level. These results suggest a consistent trading behavior of HFTs around VIX return shocks. Initiating and passive HFTs demonstrate consistent net trading in the same direction as the specific VIX shock, i.e. positive net trading after positive VIX shocks and negative net trading after negative ones. On the other side, initiating non-HFTs exhibit a trading behavior in the opposite direction to HFT for VIX shocks. Passive non-HFTs show a similar behavior though results are not significant. Comparing the results for hard information, I see two different reactions to hard information shocks: While futures return shocks induce a strong short-term reaction of HFTs, positive VIX return shocks lead to more long-term reaction and an increase in HFT net trading. Non-HFT reaction is weaker in the short run and increases in the long run for futures shocks. In contrast to HFTs, they increase their net trading in periods of low volatility.

In comparison to hard information, the reaction to soft information is different. Though both initiating HFTs and non-HFTs trade in the expected direction, non-HFTs demonstrate a significantly stronger reaction especially in the long run (0.408 as compared to 0.142 in the long run). I thus conclude that non-HFTs are able to process soft information more accurately, but need time for its interpretation. Passive traders get adversely selected and non-HFTs get less adversely selected than HFTs. An explanation for the stronger non-HFT reaction can be different trading strategies. Although the news data source is reliable and also used by trading firms[7], the actual trading strategies are not known. As proposed by Rich Brown[8] from Thomson Reuters, news

[7]cf. Thomson Reuters News Analytics Fact sheet, `http://thomsonreuters.com/content/financial/pdf/enterprise/News_Analytics.pdf`.

[8]See “The Algo who cried ‘Wolf!’ ”, Rich Brown, A-TeamGroup Publication, Oct 2009, Issue3.

ticker data can be used as a circuit breaker. By interpreting stock specific news arrival as a signal for proximate stock price volatility, a trading halt might be triggered by HFT on their arrival in order to reduce the risk of uncertainty about the following stock price reaction.

Robustness Checks

In order to check for robustness of the results for different time periods, I perform the analysis separately for time periods of high uncertainty (during the financial crisis from September 2008 to June 2009) and low uncertainty (pre- and post financial crisis). I choose time periods according to the VIX value which increased to above 30 in September 2008 and decreased again below 30 in July 2009. Results are shown in Table 3.5. The results hold for both futures shocks and VIX shocks. I can observe an even higher reaction of HFTs in the financial crisis period. This points to the theoretical finding of Foucault et al. (2013) that with increasing volatility, flow trading and thus HFT activity also increases.

Table 3.5: Impact of Information Shocks on Net Trading - Robustness over time
This table presents aggregated coefficients of HFT and non-HFT net trading after an information shock for different periods of the sample. I distinguish between the pre-crisis period (Jan-Aug 2008; Panel A1, B1, C1), the crisis period (Sep 2008-June 2009; Panel A2, B2, C2), and the post-crisis period (July 2009-Dec 2009; Panel A3, B3, C3). The VARX model is implemented with the respective trading variables as the dependent variables. The independent variables are lagged and contemporaneous HFT and non-HFT order flow and returns. All variables are aggregated into ten second intervals and standardized using mean and standard deviation for each stock and each trading day. Panel A reports aggregated impact on initiating and passive net trading for HFT (HFT_{init}, HFT_{pass}) and non-HFT ($NHFT_{init}$, $NHFT_{pass}$) as well as their respective difference ($Diff$). Panel B reports result for VIX shocks and Panel C for news events. Panel D presents differences between reaction to futures shocks and news events. SR denotes the contemporaneous impact in the short run, LR denotes the aggregated impact for the following 12 ten second intervals, i.e. 2 minutes after the information shock, $LR - SR$ denotes the long-run impact minus the short-run impact. Variables are aggregated per stock-day and tested using double clustered standard errors on stock and trading day (cf. Thompson, 2011). T-statistics are in parentheses. ***, **, and * denotes significance at the 1%, 5%, and 10% level respectively.

Table 3.5: Impact of Futures Shocks on Net Trading - continued

	Panel A1: Futures Shocks 2008 Pre-Crisis						
	Initiating Order Flow			*Passive Order Flow*			*Init+Pass*
	HFT_{init}	$NHFT_{init}$	$Diff$	HFT_{pass}	$NHFT_{pass}$	$Diff$	HFT_{all}
SR	0.087**	0.134***	-0.047	-0.007	-0.168***	0.160***	0.066**
(t-stat)	(2.17)	(6.10)	(-1.35)	(-0.30)	(-5.05)	(5.88)	(2.25)
LR	-0.184**	0.199**	-0.383***	-0.124**	-0.016	-0.109	-0.279***
(t-stat)	(-2.58)	(2.49)	(-4.47)	(-2.31)	(-0.18)	(-1.19)	(-3.94)
LR-SR	-0.271***	0.065	-0.336***	-0.117***	0.152**	-0.269***	-0.345***
(t-stat)	(-4.13)	(0.94)	(-3.98)	(-2.68)	(1.97)	(-3.29)	(-5.11)
	Panel A2: Futures Shocks 2008 Crisis						
	Initiating Order Flow			*Passive Order Flow*			*Init+Pass*
	HFT_{init}	$NHFT_{init}$	$Diff$	HFT_{pass}	$NHFT_{pass}$	$Diff$	HFT_{all}
SR	0.326***	0.218***	0.108***	-0.173***	-0.327***	0.154***	0.186***
(t-stat)	(11.49)	(17.40)	(3.62)	(-10.86)	(-17.66)	(10.01)	(8.26)
LR	0.034	0.510***	-0.476***	-0.410***	-0.257***	-0.153***	-0.307***
(t-stat)	(0.80)	(14.19)	(-12.40)	(-13.48)	(-5.56)	(-3.75)	(-9.37)
LR-SR	-0.292***	0.292***	-0.584***	-0.236***	0.071*	-0.307***	-0.493***
(t-stat)	(-8.60)	(8.56)	(-13.34)	(-10.41)	(1.86)	(-7.79)	(-15.18)
	Panel A3: Futures Shocks 2009 Post-Crisis						
	Initiating Order Flow			*Passive Order Flow*			*Init+Pass*
	HFT_{init}	$NHFT_{init}$	$Diff$	HFT_{pass}	$NHFT_{pass}$	$Diff$	HFT_{all}
SR	0.294***	0.171***	0.122***	-0.106***	-0.313***	0.207***	0.215***
(t-stat)	(4.77)	(5.19)	(2.67)	(-3.69)	(-5.46)	(4.83)	(4.21)
LR	0.145	0.279	-0.134	-0.196**	-0.300*	0.104	-0.049
(t-stat)	(1.28)	(1.36)	(-0.64)	(-2.33)	(-1.66)	(0.68)	(-0.45)
LR-SR	-0.149	0.108	-0.257	-0.090	0.014	-0.103	-0.264***
(t-stat)	(-1.52)	(0.54)	(-1.28)	(-1.12)	(0.08)	(-0.74)	(-2.81)

Table 3.5: Impact of VIX Shocks on Net Trading - continued

	Panel B1: VIX Shocks 2008 Pre-Crisis						
	Initiating Order Flow			*Passive Order Flow*			*Init+Pass*
	HFT_{init}	$NHFT_{init}$	$Diff$	HFT_{pass}	$NHFT_{pass}$	$Diff$	HFT_{all}
SR	0.021***	-0.029***	0.050***	0.014**	0.003	0.011	0.032***
(t-stat)	(2.74)	(-6.48)	(7.92)	(2.52)	(0.49)	(1.56)	(5.18)
LR	0.112***	-0.161***	0.272***	0.173***	-0.010	0.183***	0.227***
(t-stat)	(4.47)	(-6.40)	(7.86)	(8.95)	(-0.39)	(6.72)	(8.41)
LR-SR	0.091***	-0.132***	0.223***	0.159***	-0.013	0.172***	0.195***
(t-stat)	(3.70)	(-5.72)	(6.53)	(9.69)	(-0.57)	(7.17)	(7.50)
	Panel B2: VIX Shocks 2008 Crisis						
	Initiating Order Flow			*Passive Order Flow*			*Init+Pass*
	HFT_{init}	$NHFT_{init}$	$Diff$	HFT_{pass}	$NHFT_{pass}$	$Diff$	HFT_{all}
SR	0.033***	-0.020***	0.053***	0.025***	-0.018**	0.043***	0.053***
(t-stat)	(3.74)	(-3.45)	(6.42)	(4.72)	(-2.35)	(7.07)	(7.62)
LR	0.075***	-0.170***	0.245***	0.274***	-0.043	0.316***	0.284***
(t-stat)	(2.66)	(-5.44)	(6.05)	(10.19)	(-1.46)	(9.04)	(8.86)
LR-SR	0.042	-0.150***	0.192***	0.249***	-0.025	0.274***	0.231***
(t-stat)	(1.51)	(-5.22)	(5.04)	(9.81)	(-0.91)	(8.46)	(7.63)
	Panel B3: VIX Shocks 2009 Post-Crisis						
	Initiating Order Flow			*Passive Order Flow*			*Init+Pass*
	HFT_{init}	$NHFT_{init}$	$Diff$	HFT_{pass}	$NHFT_{pass}$	$Diff$	HFT_{all}
SR	0.030**	-0.012*	0.043***	0.008	-0.015	0.023***	0.041***
(t-stat)	(2.42)	(-1.94)	(3.91)	(1.12)	(-1.58)	(3.65)	(4.23)
LR	0.035	-0.169***	0.204***	0.190***	0.018	0.173***	0.187***
(t-stat)	(0.97)	(-5.21)	(5.40)	(6.44)	(0.43)	(4.74)	(5.53)
LR-SR	0.005	-0.157***	0.162***	0.182***	0.033	0.149***	0.147***
(t-stat)	(0.15)	(-5.32)	(4.82)	(6.76)	(0.88)	(4.28)	(4.94)

Table 3.5: Impact of News Shocks on Net Trading - continued

	Panel C1: News Shocks 2008 Pre-Crisis						
	Initiating Order Flow			*Passive Order Flow*			*Init+Pass*
	HFT_{init}	$NHFT_{init}$	$Diff$	HFT_{pass}	$NHFT_{pass}$	$Diff$	HFT_{all}
SR	0.028	0.048	-0.020	-0.020	-0.036	0.016	-0.011
(t-stat)	(0.48)	(0.88)	(-0.36)	(-0.31)	(-0.61)	(0.25)	(-0.21)
LR	0.217	0.309	-0.092	-0.104	-0.245	0.141	-0.018
(t-stat)	(0.65)	(1.02)	(-0.29)	(-0.48)	(-0.75)	(0.46)	(-0.07)
LR-SR	0.189	0.261	-0.072	-0.084	-0.209	0.125	-0.007
(t-stat)	(0.57)	(0.91)	(-0.23)	(-0.43)	(-0.67)	(0.45)	(-0.03)
	Panel C2: News Shocks 2008 Crisis						
	Initiating Order Flow			*Passive Order Flow*			*Init+Pass*
	HFT_{init}	$NHFT_{init}$	$Diff$	HFT_{pass}	$NHFT_{pass}$	$Diff$	HFT_{all}
SR	0.031	0.121**	-0.091*	-0.126**	-0.062	-0.064*	-0.070
(t-stat)	(0.84)	(2.35)	(-1.80)	(-2.53)	(-1.57)	(-1.76)	(-1.49)
LR	0.095	0.322**	-0.227*	-0.437**	-0.202	-0.235	-0.147
(t-stat)	(0.77)	(2.35)	(-1.71)	(-2.36)	(-1.24)	(-0.97)	(-0.99)
LR-SR	0.064	0.201	-0.137	-0.311**	-0.140	-0.171	-0.077
(t-stat)	(0.56)	(1.64)	(-1.09)	(-2.11)	(-0.86)	(-0.77)	(-0.58)
	Panel C3: News Shocks 2009 Post-Crisis						
	Initiating Order Flow			*Passive Order Flow*			*Init+Pass*
	HFT_{init}	$NHFT_{init}$	$Diff$	HFT_{pass}	$NHFT_{pass}$	$Diff$	HFT_{all}
SR	0.021	0.044	-0.023	-0.010	-0.056	0.046	0.009
(t-stat)	(0.51)	(0.76)	(-0.35)	(-0.24)	(-0.97)	(0.69)	(0.19)
LR	0.145	0.647**	-0.502	-0.693***	-0.638***	-0.055	-0.339**
(t-stat)	(1.00)	(2.06)	(-1.54)	(-3.57)	(-2.61)	(-0.19)	(-2.15)
LR-SR	0.124	0.603**	-0.479	-0.683***	-0.582**	-0.101	-0.348**
(t-stat)	(0.83)	(2.02)	(-1.53)	(-3.51)	(-2.42)	(-0.33)	(-2.15)

Furthermore, the results for futures shocks are consistent for both positive and negative shocks. Results for positive and negative shocks separately can be found in Table 3.6, Table 3.7, and Table 3.8. Interestingly, there is a stronger reaction to positive news events. On the other side, passive order flow gets adversely selected: HFTs and non-HFTs exhibit negatively directed net trading in the short and long run. Passive HFTs get less adversely selected than non-HFTs after futures return shocks in the short run, but differences are not significant. I also account for different ordering of order flows in the VARX model. The model is implemented under the assumption that HFT order flow occurs prior to non-HFT order flow. Implementing the model with reverse ordering, i.e. non-HFT order flow before HFT order flow, I see in Appendix A.2, Table A.2 that the results are not qualitatively different.

From these observations I can conclude that processing speed matters especially for hard information. The competitive edge of HFTs in speed is needed to react to hard information shocks faster and more strongly. I interpret the inverting HFT behavior shortly after the information shock as a strategy to realize profits from this shock. The non-HFT group is slower and also trades on hard information for a longer time period or new soft information which is harder to interpret and involves more risk in the interpretation. This leads to the question whether HFTs actually do cream-skimming since they aggressively trade on information within the first ten seconds after information arrivals which would also be processed by non-HFTs with a longer time period and less volume. This trading strategy could also cause a stronger overreaction to information events and make price efficiency deteriorate. Furthermore, the analysis of VIX shocks as well as the robustness check for periods of high and low volatility provide evidence that HFTs trade more actively and engage more in the processing of hard information in periods of high volatility.

Table 3.6: Impact of Positive and Negative Futures Shocks on Net Trading
This table presents coefficients of HFT and non-HFT net trading after arrival of an exogenous hard information event, proxied by abnormally high and low returns of the S&P 500 futures. The VARX model is implemented with respective trading variables as the dependent variables. The independent variables are lagged and contemporaneous HFT and non-HFT order flow and returns. All variables are aggregated into ten second intervals and standardized using mean and standard deviation for each firm and each trading day. Panel A reports aggregated impact on initiating net trading for HFT (HFT_{init}) and non-HFT ($NHFT_{init}$) to abnormally high and low futures shocks as well as their respective difference ($Diff$). Panel B reports aggregated impact on passive net trading for HFT (HFT_{pass}) and non-HFT ($NHFT_{pass}$). SR denotes the contemporaneous impact in the short run, LR denotes the aggregated impact for the following 12 ten second intervals, i.e. 2 minutes after the information shock, $LR - SR$ denotes the long-run impact minus the short-run impact. Variables are aggregated per stock-day and tested using double clustered standard errors on stock and trading day (c.f. Thompson, 2011). T-statistics are in parentheses. ***, **, and * denotes significance at the 1%, 5%, and 10% level respectively.

	Panel A: Positive Futures Shocks					
	Initiating Order Flow			*Passive Order Flow*		
	HFT_{init}	$NHFT_{init}$	$Diff$	HFT_{pass}	$NHFT_{pass}$	$Diff$
SR	0.268***	0.195***	0.073**	-0.115***	-0.296***	0.181***
(t-stat)	(8.71)	(11.73)	(2.51)	(-6.68)	(-11.70)	(9.38)
LR	-0.046	0.377***	-0.424***	-0.307***	-0.156**	-0.151***
(t-stat)	(-0.95)	(5.21)	(-5.62)	(-7.71)	(-2.55)	(-2.72)
LR-SR	-0.314***	0.182***	-0.496***	-0.192***	0.139***	-0.331***
(t-stat)	(-7.09)	(2.69)	(-6.46)	(-5.46)	(2.67)	(-6.24)

	Panel B: Negative Futures Shocks					
	Initiating Order Flow			*Passive Order Flow*		
	HFT_{init}	$NHFT_{init}$	$Diff$	HFT_{pass}	$NHFT_{pass}$	$Diff$
SR	-0.258***	-0.193***	-0.065**	0.107***	0.299***	-0.192***
(t-stat)	(-8.54)	(-13.25)	(-2.41)	(6.67)	(12.40)	(-10.71)
LR	-0.022	-0.340***	0.317***	0.210***	0.217***	-0.007
(t-stat)	(-0.51)	(-6.24)	(5.50)	(5.80)	(3.62)	(-0.13)
LR-SR	0.236***	-0.147***	0.382***	0.103***	-0.082	0.185***
(t-stat)	(5.93)	(-2.83)	(5.85)	(3.38)	(-1.54)	(3.58)

Table 3.7: Impact of Positive and Negative Volatility Shocks on Net Trading
This table presents coefficients of HFT and non-HFT net trading after arrival of an exogenous hard information event, proxied by abnormally high and low VIX returns. The VARX model is implemented with respective trading variables as the dependent variables. The independent variables are lagged and contemporaneous HFT and non-HFT order flow and returns. All variables are aggregated into ten second intervals and standardized using mean and standard deviation for each stock and each trading day. Panel A reports aggregated impact on initiating net trading for HFT (HFT_{init}) and non-HFT ($NHFT_{init}$) to abnormally high and low VIX shocks as well as their respective difference ($Diff$). Panel B reports aggregated impact on passive net trading for HFT (HFT_{pass}) and non-HFT ($NHFT_{pass}$). SR denotes the contemporaneous impact in the short run, LR denotes the aggregated impact for the following 12 ten second intervals, i.e. 2 minutes after the information shock, $LR - SR$ denotes the long-run impact minus the short-run impact. Variables are aggregated per stock-day and tested using double clustered standard errors on stock and trading day (c.f. Thompson, 2011). T-statistics are in parentheses. ***, **, and * denotes significance at the 1%, 5%, and 10% level respectively.

	Panel A: Positive VIX Shocks					
	Initiating Order Flow			*Passive Order Flow*		
	HFT_{init}	$NHFT_{init}$	$Diff$	HFT_{pass}	$NHFT_{pass}$	$Diff$
SR	0.026***	-0.019***	0.045***	0.010**	-0.006	0.015***
(t-stat)	(3.52)	(-4.99)	(7.54)	(2.09)	(-0.93)	(2.97)
LR	0.081***	-0.128***	0.209***	0.183***	-0.031	0.215***
(t-stat)	(3.59)	(-5.78)	(7.47)	(8.68)	(-1.39)	(8.71)
LR-SR	0.055**	-0.109***	0.164***	0.174***	-0.026	0.200***
(t-stat)	(2.52)	(-5.18)	(6.11)	(8.83)	(-1.19)	(8.92)

	Panel B: Negative VIX Shocks					
	Initiating Order Flow			*Passive Order Flow*		
	HFT_{init}	$NHFT_{init}$	$Diff$	HFT_{pass}	$NHFT_{pass}$	$Diff$
SR	-0.035***	0.016***	-0.051***	-0.018***	0.017***	-0.036***
(t-stat)	(-4.33)	(3.62)	(-6.87)	(-3.78)	(2.73)	(-6.39)
LR	-0.089***	0.151***	-0.240***	-0.169***	0.015	-0.185***
(t-stat)	(-3.74)	(6.42)	(-7.90)	(-8.66)	(0.65)	(-6.97)
LR-SR	-0.055**	0.134***	-0.189***	-0.151***	-0.002	-0.149***
(t-stat)	(-2.55)	(6.33)	(-6.83)	(-8.45)	(-0.09)	(-6.23)

Table 3.8: Impact of Positive and Negative News Shocks on Net Trading

This table presents aggregated coefficients of HFT and non-HFT net trading after the arrival of an exogenous soft information event, proxied by positive and negative news events. The VARX model is implemented with respective trading variables as the dependent variables. The independent variables are lagged and contemporaneous HFT and non-HFT order flow and returns. All variables are aggregated into ten second intervals and standardized using mean and standard deviation for each firm and each trading day. Panel A reports aggregated impact on initiating net trading for HFT (HFT_{init}) and non-HFT ($NHFT_{init}$) after news arrivals as well as their respective difference ($Diff$). Panel B reports aggregated impact on passive net trading for HFT (HFT_{pass}) and non-HFT ($NHFT_{pass}$). SR denotes the contemporaneous impact in the short run, LR denotes the aggregated impact for the following 12 ten second intervals, i.e. 2 minutes after news arrival, $LR - SR$ denotes the long-run impact minus the short-run impact. Variables are aggregated per stock-day and tested using double clustered standard errors on stock and trading day (c.f. Thompson, 2011). T-statistics are in parentheses. ***, **, and * denotes significance at the 1%, 5%, and 10% level respectively.

	Panel A: Positive News Shocks					
	Initiating Order Flow			*Passive Order Flow*		
	HFT_{init}	$NHFT_{init}$	$Diff$	HFT_{pass}	$NHFT_{pass}$	$Diff$
SR	0.077**	0.105**	-0.028	-0.095*	-0.084**	-0.011
(t-stat)	(2.19)	(2.01)	(-0.53)	(-1.90)	(-2.23)	(-0.27)
LR	0.133	0.705***	-0.572***	-0.704***	-0.475*	-0.230
(t-stat)	(0.93)	(2.72)	(-2.87)	(-4.48)	(-1.87)	(-1.12)
LR-SR	0.056	0.600***	-0.544***	-0.610***	-0.391	-0.219
(t-stat)	(0.41)	(2.65)	(-3.12)	(-4.68)	(-1.63)	(-1.11)

	Panel B: Negative News Shocks					
	Initiating Order Flow			*Passive Order Flow*		
	HFT_{init}	$NHFT_{init}$	$Diff$	HFT_{pass}	$NHFT_{pass}$	$Diff$
SR	0.014	-0.055*	0.069**	0.044	0.022	0.022
(t-stat)	(0.44)	(-1.67)	(2.03)	(1.26)	(0.67)	(0.64)
LR	0.009	-0.084	0.093	0.158	0.217	-0.060
(t-stat)	(0.08)	(-0.47)	(0.49)	(1.20)	(1.00)	(-0.28)
LR-SR	-0.004	-0.029	0.024	0.114	0.195	-0.081
(t-stat)	(-0.04)	(-0.18)	(0.14)	(0.97)	(0.93)	(-0.40)

3.3.3 Influence of Information Events on Price Discovery

I discussed different effects of information events on net trading in Section 3.3.2. In the following section, I further analyze which group of traders has a stronger influence on price discovery around the studied information events. The second model takes a closer look at informed trading of different trader groups by incorporating interaction variables according to Tookes (2008). I restrict the models to periods after the information shock and use variables aggregated to ten second intervals.

The VAR model is implemented as follows:

$$
\begin{aligned}
V_{i,t}^{h} &= \alpha_i^h + \sum_{j=1}^{k} \beta_{i,j}^{h} V_{i,t-j}^{h} + \sum_{j=0}^{k} \gamma_{i,j}^{h} V_{i,t-j}^{n} + \sum_{j=0}^{k} \delta_{i,j}^{h} r_{i,t-j} \\
&\quad + \sum_{w=1}^{W} D_{i,w} \Big(\sum_{j=1}^{k} \beta_{i,j}^{h,w} V_{i,t-j}^{h} + \sum_{j=0}^{k} \gamma_{i,j}^{h,w} V_{i,t-j}^{n} + \sum_{j=0}^{k} \delta_{i,j}^{h,w} r_{i,t-j} \Big) + \epsilon_{i,t}^{h} \\
V_{i,t}^{n} &= \alpha_i^n + \sum_{j=0}^{k} \beta_{i,j}^{n} V_{i,t-j}^{h} + \sum_{j=1}^{k} \gamma_{i,j}^{n} V_{i,t-j}^{n} + \sum_{j=0}^{k} \delta_{i,j}^{n} r_{i,t-j} \\
&\quad + \sum_{w=1}^{W} D_{i,w} \Big(\sum_{j=0}^{k} \beta_{i,j}^{n,w} V_{i,t-j}^{h} + \sum_{j=1}^{k} \gamma_{i,j}^{n,w} V_{i,t-j}^{n} + \sum_{j=0}^{k} \delta_{i,j}^{n,w} r_{i,t-j} \Big) + \epsilon_{i,t}^{n} \\
r_{i,t} &= \alpha_i^r + \sum_{j=0}^{k} \beta_{i,j}^{r} V_{i,t-j}^{h} + \sum_{j=0}^{k} \gamma_{i,j}^{r} V_{i,t-j}^{n} + \sum_{j=1}^{k} \delta_{i,j}^{r} r_{i,t-j} \\
&\quad + \sum_{w=1}^{W} D_{i,w} \Big(\sum_{j=0}^{k} \beta_{i,j}^{r,w} V_{i,t-j}^{h} + \sum_{j=0}^{k} \gamma_{i,j}^{r,w} V_{i,t-j}^{n} + \sum_{j=1}^{k} \delta_{i,j}^{r,w} r_{i,t-j} \Big) + \epsilon_{i,t}^{r}
\end{aligned}
\tag{3.2}
$$

The model specifications in Equation (3.2) is the same as in Equation (3.1); only the interaction terms are added. The value of $D_{i,w}$ is +1 if an information events occurs and 0 otherwise. I test whether in times with information events, HFT and non-HFT order flow has a significant influence on stock returns. I estimate the equations separately using OLS for all three information events.

Results of the VAR model in Equation (3.2) for the respective information events (i.e. futures return shocks, VIX return shocks, and news shocks) are presented in Table 3.9. The estimates represent the sum of the overall influence of HFT and NHFT net trading on returns plus the *additional* influence after the occurrence of an information shock. Panel A represents results for the influence of initiated and passive HFT net trading influence after the occurrence of a futures return shock. Panel B represents results for VIX return shocks, and Panel C for news events.

Positive and negative information events, such as a positive or negative return shock or news, should steer the aggregate order flow in the same direction, i.e. more buy orders after positive events and more sell orders after negative events. While HFTs dominate the price discovery in the short run, the dominance decreases for futures and VIX shocks and inverts for news events. With regard to the overall influence of news shocks on stock returns as presented in Table 3.3, I have shown that the main impact of news events on stock returns occurs after 10 seconds of the event. In this context, the influence on stock returns paints a consistent picture of initiating non-HFTs contributing to price discovery around 8% more than HFTs (which economically significant, however not statistically).

With respect to the passive order flow after information shocks, both groups of traders get adversely selected in the short run, reflected in the negative influences on stock returns. On the long run however, HFT as well as non-HFT influence on stock returns becomes positive in the long run (10.5% for futures shocks and 9.7% for VIX shocks[9]). Interestingly, passive non-HFTs consistently demonstrate a higher contribution to price discovery in the long run than HFTs. I conclude that passive trading strategies follow the change in order flow and prices after information events in the long run.

This is an interesting aspect for the price discovery discussion about the level of information of initiating and passive orders: While previous literature has suggested that passive limit orders are more informed, I can contribute to this statements with a more differentiated analysis. While initiating marketable orders, especially by HFTs, dominate price discovery in the short run, i.e. within a period of 10 seconds, passive non-HFT orders are more informed in the long run. This finding holds for periods without information events as well as for the additional influences after the occur-

[9]A differentiation between positive and negative VIX shocks does not yield qualitatively different results, though coefficients for positive VIX shocks are generally higher than for negative VIX shocks.

Table 3.9: Influence of Trading after Information Shocks on Price Discovery
This table presents regression results of the VAR model in Equation (3.2). The dependent variable is the respective trade variable. The independent variables are lagged and contemporaneous HFT and non-HFT order flow and returns as well as interaction variables of the independent variables and a dummy for the respective information shock. The full set of equations are estimated separately by OLS. Panel A reports results for net trading of HFT (HFT_{pass}) and non-HFT ($NHFT_{pass}$) for all periods and periods after S&P 500 futures return shocks, Panel B periods of VIX return shocks and Panel C periods of news arrivals. All variables are aggregated into ten second intervals and standardized using mean and standard deviation for each stock and each trading day. SR denotes the contemporaneous influence in the short run, LR denotes the aggregated influence for the following 12 ten second intervals, i.e. 2 minutes after news arrival, $LR - SR$ denotes the long-run influence minus the short-run influence. Variables are tested with Wald test. ***, **, and * denotes significance at the 1%, 5%, and 10% level respectively.

	Panel A: Influence on Stock Returns after Futures Shocks					
	Initiating Order Flow			*Passive Order Flow*		
	HFT_{init}	$NHFT_{init}$	$Diff$	HFT_{pass}	$NHFT_{pass}$	$Diff$
SR	0.349***	0.307***	0.042***	-0.255***	-0.394***	0.140***
LR	0.215***	0.162***	0.053***	-0.150***	-0.230***	0.079***
LR-SR	-0.134***	-0.146***	0.012***	0.105***	0.165***	-0.060***

	Panel B: Influence on Stock Returns after VIX Shocks					
	Initiating Order Flow			*Passive Order Flow*		
	HFT_{init}	$NHFT_{init}$	$Diff$	HFT_{pass}	$NHFT_{pass}$	$Diff$
SR	0.342***	0.321***	0.021***	-0.263***	-0.383***	0.119***
LR	0.213***	0.188***	0.025***	-0.166***	-0.234***	0.068***
LR-SR	-0.129***	-0.133***	0.004	0.097***	0.149***	-0.051***

	Panel C: Influence on Stock Returns after News Events					
	Initiating Order Flow			*Passive Order Flow*		
	HFT_{init}	$NHFT_{init}$	$Diff$	HFT_{pass}	$NHFT_{pass}$	$Diff$
SR	0.396***	0.338***	0.059***	-0.356***	-0.352***	-0.003***
LR	0.211***	0.232	-0.021	-0.267***	-0.163***	-0.104*
LR-SR	-0.186***	-0.106***	-0.080	0.088**	0.189***	-0.101

rence of information events.

In summary, initiating and passive traders complement each other in the price discovery process since initiating traders lead price discovery in the short run, while passive non-HFTs have a higher influence on market returns in the long run. Furthermore, I find that hard information has significant effects on HFT and non-HFT order flow and price discovery in the short and long run. Soft information is impounded in a longer amount of time than 10 seconds as shown in Section 3.3.2. Thus, long-run effects are more representative of the price discovery process and indicate a dominance of non-HFTs in processing soft information and impounding it into stock prices.

3.3.4 Influence of Information Events on Trading Profits

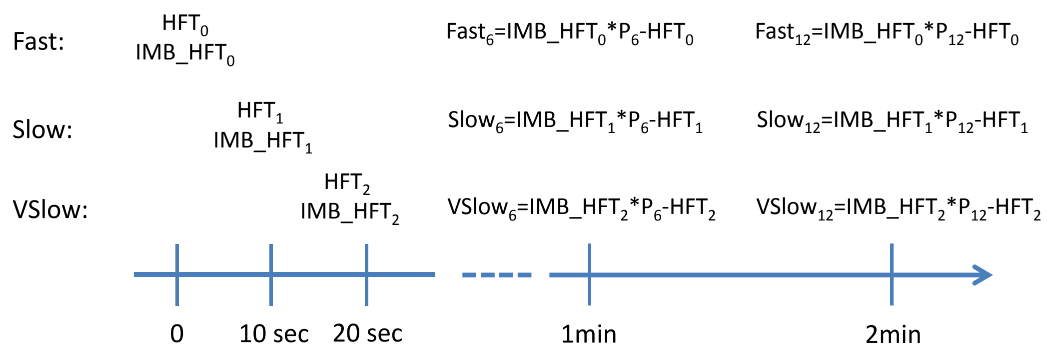
In this section, I use HFT profits to characterize the different information events. I adapt profit measures based on Menkveld (2013) and Brogaard et al. (2013). Specifically, I assume that HFTs start with zero inventory at the occurrence of the information shock ($t = 0$) and cumulate profit after the shock ($t = 1, ..., 12$). This measure is denoted *Real* in the results in Table 3.10. In the spirit of Menkveld (2013) and Brogaard et al. (2013), *Real* can be further decomposed into a "positioning" profit and a cash flow profit,

$$Real_t = \sum_{i=0}^{t} IMB\_HFT_i * P_T - \sum_{i=0}^{t} HFT_t, \tag{3.3}$$

where t denotes the 10 second interval, IMB_HFT_t is the closing imbalance (number of shares bought minus number of shares sold) of HFT trades in number of shares at the end of t, P_T is the closing quote midpoint at the end of t in dollars, and HFT_t is HFT net trading in dollars (buy volume minus sell volume). I distinguish between initiated and passive trades for HFT imbalance ($IMB\_HFT_{init,t}$, $IMB\_HFT_{pass,t}$) and net trading ($HFT_{init,t}$, $HFT_{pass,t}$). Since participants of a trade are exhaustively indexed as either HFT or non-HFT, this also implies that the non-HFT profit is the negative of HFT profit.

I further compute fictitious profits that would have been realized from trading only in the ten second interval in which the information shock occurs (*Fast*), in the time interval 10 seconds after the shock occurs ($Slow$) and 20 seconds after the shock occurs ($VSlow$). The computed formulas are presented in Figure 3.5 below. The values are aggregated per stock-day and tested using robust standard errors clustered by stock and trading day (cf. Thompson, 2011).

Figure 3.5: Calculation of Fictitious Profits



I account for NASDAQ trading fees and rebates in my analysis.[10] Results in Table 3.10 present the profits yielded after information shocks from the closing imbalances IMB_HFT_0, IMB_HFT_1 and IMB_HFT_2 and net trading HFT_0, HFT_1 and HFT_2 in \$. The left hand side presents results for initiating HFT and the right hand side for passive HFT.

[10] Analyses without trading fees and rebates do not yield qualitatively different results.

Table 3.10: HFT Profits after Information Shocks

This table presents HFT profits after information events. Panel A shows profits after futures shocks, Panel B for VIX shocks, and Panel C for news shocks. *Real* denotes the total realized trading profit of initiating and passive HFT under the assumption that they start with zero inventory at the occurrence of the information shock. *Fast*, *Slow*, and *VSlow* are fictitious profits under the assumption that HFT: (1) start at occurrence of an information shock with 0 inventory, (2) only make trades 0 seconds (*Fast*), 10 seconds (*Slow*), and 20 seconds (*VSlow*) after the information event, and (3) sell their inventory 60 seconds or 120 seconds after the information event. All profit variables are in $, aggregated per stock-day, and tested using robust standard errors clustered by stock and trading day. T-statistics are in parentheses. ***, **, and * denotes significance at the 1%, 5%, and 10% level respectively.

	Panel A: Futures Shock								
	Initiating Volume				*Passive Volume*				*All*
	Real	*Fast*	*Slow*	*VSlow*	*Real*	*Fast*	*Slow*	*VSlow*	
0 sec	556.15***	556.15***			-174.69***	-174.69***			381.46***
(*t*-stat)	(5.30)	(5.30)			(-3.27)	(-3.27)			(4.13)
10 sec	632.76***	369.68***	261.19***		-266.40***	-148.61***	-115.53***		366.36***
(*t*-stat)	(5.90)	(5.86)	(5.71)		(-3.71)	(-3.97)	(-3.30)		(4.13)
20 sec	630.94***	292.37***	138.46***	200.20***	-310.41***	-115.09***	-94.47***	-101.01***	320.53***
(*t*-stat)	(6.14)	(6.12)	(4.86)	(5.97)	(-3.65)	(-3.80)	(-3.36)	(-3.45)	(4.09)
60 sec	654.82***	154.21***	75.99***	77.75***	-426.13***	-65.53***	-57.68***	-61.46***	228.70***
(*t*-stat)	(6.06)	(5.25)	(5.05)	(5.82)	(-4.02)	(-3.35)	(-3.72)	(-3.90)	(3.18)
120 sec	676.22***	90.64***	50.13***	44.15***	-473.88***	-33.82**	-38.47***	-27.54**	202.34*
(*t*-stat)	(4.68)	(4.22)	(3.10)	(3.35)	(-3.85)	(-2.18)	(-3.27)	(-2.27)	(1.79)

Panel B: VIX Shock									
	Initiating Volume				*Passive Volume*				*All*
	Real	*Fast*	*Slow*	*VSlow*	*Real*	*Fast*	*Slow*	*VSlow*	
0 sec	264.27***	264.27***			-104.05***	-104.05***			160.21***
(*t*-stat)	(5.77)	(5.77)			(-3.31)	(-3.31)			(3.67)
10 sec	483.74***	262.97***	219.22***		-211.70***	-124.26***	-85.45**		272.04***
(*t*-stat)	(5.88)	(5.96)	(5.41)		(-3.50)	(-4.13)	(-2.50)		(3.58)
20 sec	606.78***	194.61***	220.40***	191.78***	-316.90***	-90.31***	-128.53***	-98.07***	289.88***
(*t*-stat)	(6.07)	(6.33)	(5.47)	(5.39)	(-3.90)	(-3.03)	(-4.18)	(-4.01)	(3.85)
60 sec	784.33***	120.43***	91.64***	94.18***	-512.75***	-57.83***	-73.51***	-75.27***	271.58***
(*t*-stat)	(6.29)	(6.11)	(4.81)	(4.22)	(-4.43)	(-3.19)	(-4.29)	(-4.42)	(3.44)
120 sec	962.52***	75.26***	67.68***	64.95***	-651.26***	-29.35***	-44.51***	-50.51***	311.26***
(*t*-stat)	(6.05)	(3.53)	(3.97)	(4.24)	(-4.38)	(-3.01)	(-3.34)	(-3.96)	(2.85)

Panel C: News Shock									
	Initiating Volume				*Passive Volume*				*All*
	Real	*Fast*	*Slow*	*VSlow*	*Real*	*Fast*	*Slow*	*VSlow*	
0 sec	10.43***	10.43***			-15.03***	-15.03***			-4.60
(*t*-stat)	(3.02)	(3.02)			(-3.14)	(-3.14)			(-1.04)
10 sec	17.76	5.54	12.14*		19.86	23.87	-3.89		37.62**
(*t*-stat)	(0.48)	(0.15)	(1.93)		(0.41)	(0.49)	(-0.75)		(2.27)
20 sec	34.82	0.45	6.59	27.79*	26.98	21.72	3.39	1.86	61.80*
(*t*-stat)	(0.78)	(0.01)	(0.40)	(1.81)	(0.54)	(0.45)	(0.24)	(0.23)	(1.87)
60 sec	55.29*	18.87**	-2.49	-10.57	-16.59	1.36	9.86	14.20	38.71
(*t*-stat)	(1.77)	(2.09)	(-0.11)	(-0.98)	(-0.47)	(0.07)	(0.56)	(1.21)	(1.02)
120 sec	136.31**	27.19***	25.26	2.17	-76.39	-1.42	4.93	11.05	59.93
(*t*-stat)	(2.03)	(2.66)	(1.01)	(0.30)	(-1.30)	(-0.12)	(0.34)	(0.77)	(1.28)

The profit results support results on trading reaction. In terms of the characterization of the different information shocks, I can see clear differences: Futures shocks imply a strong and decreasing reaction in realized trading profits. In terms of HFT reaction, speed is vital: Profits from fast reaction (\$556.15) deteriorates by more than 30% if realized after 10 seconds and only yields one sixth of the actually realized profit after two minutes. Compared to profits from slower reaction to information events (\$261.19 for $Slow$ and \$200.20 $VSlow$), the profits are less than half of the profits of fast HFTs. On the other side, passive HFTs get adversely selected which is also reflected in their profits. In total, HFTs gain their highest profits in the short run directly after the shock and their profits monotonously decrease. VIX shocks yield similar results to futures shocks, but differently to futures shocks, the initiating profits as well as the total profits are increasing.

News shocks induce weaker reactions in realized trading profits in absolute terms, but profits are increasing in the long run. The interesting result here is that despite high adverse selection losses of passive trades, HFTs are able to gain positive profits in total. Additionally, profits of slower trades are higher than those of fast trades which can be explained that HFTs wait for the market reaction before actually trading on soft information.

In terms of profits, non-HFTs experience disadvantages for both hard and soft information: They do not realize short-term profits on hard information since HFTs are faster in processing this type of information. Furthermore, they do not seize profit opportunities available in periods of high volatility, but increase their net trading in periods of low volatility when profits are low. Additionally, for soft information shocks, HFTs are able to interpret market reaction comparably fast and gain positive profits within the twenty second period after the news event.

A differentiation between crisis, pre-crisis, and post-crisis periods (for a definition of the periods see Section 3.3.2) gives insight into profit opportunities in the respective time period. Results are presented in Table A.3. Profit opportunities after futures shocks are higher during the financial crisis and more short-lived. In the crisis period, realized as well as fictitious trading profits are decreasing within two minutes while they are increasing in the other time periods. Consequently, the importance of speed is even higher in crisis periods with high volatility. Similar to the total results, *Fast* yields the highest profit compared to *Slow* and *VSlow*. Apart from the fact that profit opportunities are more short-lived in the crisis period, the results do not yield qualitatively different results.

There are several limitations to this study. I do not test for causality in the analyses. Therefore, the results are restricted to the impact on specific trade variables after controlling for specified lagged variables. I use a relatively short time period after the information events though the applied models are robust to different time lags. Furthermore, I discuss possible correlations between information events in Section 3.2 and do not find any relevant interrelationships between the chosen events. Further research should be done to include other information events, such as earnings announcements and macroeconomic news. An in-depth analysis at the 1 second-level as well as longer time periods might be important in order to make inferences on the exact duration of the information impacts.

3.4 Summary

I analyze the impact of different kinds of information events on HFT and non-HFT, on price discovery as well as on trading profits for short and long time periods. I follow the classification of hard quantitative and soft qualitative information shocks by Petersen (2004). Based on the analysis of futures return shocks as well as news events, I find that information processing in financial markets is split into two speed domains: The high frequency world is dominated by HFT that trade on hard information shocks within a short time period. This dominance is also reflected in the short-term price discovery and short-term trading profits. On the other side, the non-high frequency world is still dominated by non-HFTs that process soft information and lead long-run price discovery.

Recent developments have shown a trend towards machine-processable news and a general hardening of soft information. In addition to existing concerns associated with HFT, these algorithms might give rise to even greater concerns than traditional HFT algorithms due to misinterpretation of and overreaction to events. In my analysis, I cannot confirm this development although my analysis is limited to a data sample from 2008 to 2009. My results might ease some of these concerns towards soft information processing, but also point to an edge of HFTs over non-HFTs in the speed of hard information processing. Thus, I cannot draw a consistently positive or negative image for HFT overall, but provide a more differentiated insight with respect to differentiation of initiating and passive trading, the effect on different time frequencies, and hard and soft information.

Chapter 4

HFT and Human Trading Behavior

Discussions on HFT are controversial with respect to whether the impact of HFT on market quality and retail traders are overly positive or negative. Proponents emphasize the overall positive effects on financial markets, such as lower transaction costs as well as higher liquidity and efficiency, that also retail traders benefit from (Financial Times, 2009). Opponents argue that due to the superior speed and processing power of HFTs, ordinary investors would be "left in the dust" (Wall Street Journal, 2011a) when put into competition with HFTs. Empirical literature so far has focused on the overall effects of HFT on market quality and efficiency, while the impact on human trading behavior is difficult to identify. Another 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 order to systematically investigate the impact of computer trading on markets and trading behavior, I conduct a controlled lab experiment. Experiments are an underused method in finance (c.f. Bloomfield and Anderson, 2010), mostly due to their limited external validity. Conducting experiments can, however, serve as a complementary approach where field data cannot be obtained and where there is a lack of observability. Both conditions apply when aiming at isolating the gradual effect of computer trading on trading behavior and overall market efficiency. To the best of my knowledge, this is the first experiment with physiological measurements that investigates a financial market setting with both trading agents and human participants.

In this experiment, I focus specifically on three questions: (1) whether the interaction of human traders with computer agents has a systematic influence on their trading behavior and (2) on their emotional state, and (3) whether this influence translates into differences in market outcome. I distinguish between computer agents with different trading speed. Moreover, I measure the participants' heart rates as proxies for their overall level of emotional arousal as well as intensities of emotional responses to specific market events.

I find that the presence of slow trading agents leads to a decrease of price aggressiveness and to a slight increase in market efficiency. This is due to the lower level of competitiveness of human traders against computer agents than against other human traders. The introduction of fast trading agents however increases the time pressure on human traders and thus increases their price aggressiveness. Furthermore, I find that the human traders' emotional states are affected by the presence of computer agents as well as their speed. Physiological measurement allows to make inferences on the emotional state of human traders in different market settings. Results of heart rate measurement are consistent with the findings for trading behavior, but allow deeper insight into the underlying visceral processes when humans interact with agents of different speed: While fast trading agents induce a higher level of arousal due to an increasing "time pressure", slower agents cause a "de-emotionalization" of human participants and thus a lower level of arousal than in human-only markets.

From the results, I can make inferences on the reaction of human traders in their reaction and emotional arousal to the presence and speed of trading agents. In the experiment, the market is transparent to the extent that the number of trading agents is known ex ante, but the counterparties of the transactions are not revealed. The amount of HFT is quantified at around 50% of the overall equity trading volume in the U.S. (Sussman, 2012) and the identity of counterparties is not revealed. Thus, I argue that this setting provides a similar context with respect to the level of transparency that is provided to human traders in real-world financial markets. Consistent with empirical literature on HFT, I find that trading agents have a positive effect on efficiency and liquidity (cf. Hendershott et al., 2011; Chaboud et al., 2013). The experimental environment also allows to draw inferences on individual trading behavior and emotional arousal: While the presence of slow agents leads to a decrease of price aggressiveness and emotional arousal, fast agents induce higher aggressiveness and arousal.

4.1 Related Literature and Hypothesis Development

There are several strands of literature that are related to this paper, specifically in the areas experimental finance and NeuroIS as well as market microstructure and mechanism design, but also to psychological research. In this experiment, I am specifically interested in the impact of computer agent presence on trading behavior and arousal and how behavioral differences translate into differences in market efficiency and liquidity. To explain the differences in arousal and trading behavior, I draw inferences from psychological literature on "competitive arousal". As argued by Ku et al. (2005), "competitive arousal" involves factors such as "rivalry, social facilitation, time pressure, and/or the uniqueness of being first" which can fuel arousal and possibly impair decision-making. I combine this line of literature with the strand of market microstructure literature on trading aggressiveness and market quality and draw methodological links to experimental finance and economics and NeuroIS.

4.1.1 Experimental and Neuro Finance

This study is closely related to experimental studies with a focus on behavioral biases and market design issues as well as their effects on market quality. Bloomfield et al. (2009) introduce noise traders to their experimental market that mostly follow contrarian strategies. This leads to an increase in market volume and liquidity. I similarly introduce trading agents to the experimental markets which follow a profit maximization strategy. This leads to increases in market volume and liquidity as well. In the context of emotional arousal and excitement, Andrade et al. (2012) provide evidence of larger asset bubbles in experimental markets where participants are shown exciting videos before. In the experimental markets, I find different levels of emotional arousal across treatments, which are not induced by videos or pictures but are integral to the trading task. The different levels of arousal in this experiment can thus be isolated as a result from the varying number of trading agents as well as the differences in market conditions.

Within the last ten years, researchers also started to draw upon the advances in cognitive neuroscience in order to gain a deeper understanding of the traders' emotional processes. Due to the dynamic interaction in markets, most of the studies that focus on competitive market interaction build on psychophysiological parameters as these can be collected for several individuals simultaneously. Among the first, Lo and Repin (2002) measure psychophysiological parameters of professional security traders during live trading sessions in the field. The authors find that traders exhibit emotional responses to market events and that senior traders show a different pattern of emotional arousal than junior traders. Similarly, Fenton-O'Creevy et al. (2012) find that experienced traders exhibit a higher degree of heart rate variability, which can be interpreted as a higher individual capacity for emotion regulation. Based on heart rate measurements, Smith and Dickhaut (2005) provide evidence that the design of the market mechanism has an influence on the degree of emotions experienced by market participants. Building on these results, Adam et al. (2013) find that arousal can in fact mediate the impact of market design on human behavior.

As argued by Ku et al. (2005), interaction with other humans can induce competitive arousal in the human traders which is driven by social facilitation, time pressure, and rivalry. These higher levels of arousal are known to push humans to deviate from previously chosen strategies and to increase their willingness to take risk (e.g. Maule et al., 2000). With the increasing presence of computerized trading agents in financial markets though, both social facilitation and rivalry may be less intense. As a result, the human traders' arousal levels as well as their impact on trading behavior may be mitigated. In this context, Teubner et al. (2012) find in an auction lab experiment that human bidders exhibit less arousal and experience emotions less intensely when they are facing computerized rather than human opponents. It is important to highlight that their experiment focused on static first-price sealed-bid auctions. In contrast, this study investigates the dynamic interaction of traders in continuous double auctions. Thus, I concentrate on the following research questions in Section 4.5.1 and 4.5.2:

Research Question 4a: *Are humans more or less emotionally aroused when trading against computer agents than against other humans?*

Research Question 4b: *Do differences in emotional arousal affect trading behavior?*

4.1.2 Market Microstructure and Mechanism Design

The experimental design is oriented along the classic experiments of Smith (1962) and Gode and Sunder (1993). In his seminal work in experimental economics, Smith (1962) demonstrates the efficiency of the double auction mechanism in different experimental market settings. A double auction allows buyers and sellers to submit their buy orders (bids) or sell orders (asks) continuously and asynchronously at any time during a trading period. The market design is closely related to his setting in order to reduce effects that are common for other market designs, such as information processing activities (e.g. Plott and Sunder, 1988) or behavioral biases such as the disposition effect (Weber and Camerer, 1998) or overconfidence (Biais et al., 2005). A similar design is applied by Gode and Sunder (1993) who conduct double auction experiments for human participants and zero intelligence (ZI) traders separately. They demonstrate that the combination of the double auction design and the budget constraint of otherwise irrational trading agents still leads to a convergence of transaction prices towards the equilibrium price and thus an efficient market outcome.

In order to provide a more realistic scenario of competition against trading agents in the context of AT and HFT, I apply zero intelligence plus (ZIP) agents in this experiment. The ZIP algorithm, developed by Cliff and Bruten (1997b) as a response to the Gode and Sunder (1993) experiment, is a learning algorithm that yields a better performance in double auction markets by executing simple profit maximization (see Section 4.3.4 for details). There are several demonstrations that ZIP agents achieve a higher trading performance in competition with human traders for fast as well as slow trading speeds (cf. Das et al., 2001). However, economic implications were restricted due to limited number of observations and the complexity of the market design.

The results are further related to the increasing literature on HFT and AT. Hendershott et al. (2011) show that an increase in AT leads to higher market liquidity. Chaboud et al. (2013) provide evidence that AT improve market efficiency in FX markets by executing triangular arbitrage strategies. I find similar results in this experiment. The experimental analysis also provides further insight into human trading behavior and emotions which would be difficult to obtain in a real world scenario.

Consequently, it is important to understand the influence of human trading behavior on final market outcome. I focus on outcome measures in terms of market quality, specifically efficiency and liquidity, and draw connections to recent empirical HFT literature. Thus, the following research question is answered in Section 4.5.3.

> **Research Question 4c:** *Do differences in human trading behavior in turn translate into differences in market quality?*

4.2 A Market Framework for Human-Computer Interaction

In order to measure human emotions in economic laboratory experiments, I apply the psychophysiological measurement as proposed by Adam et al. (2011). I further 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 4.1.

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., 2010; Dimoka, 2010; Adam et al., 2013).

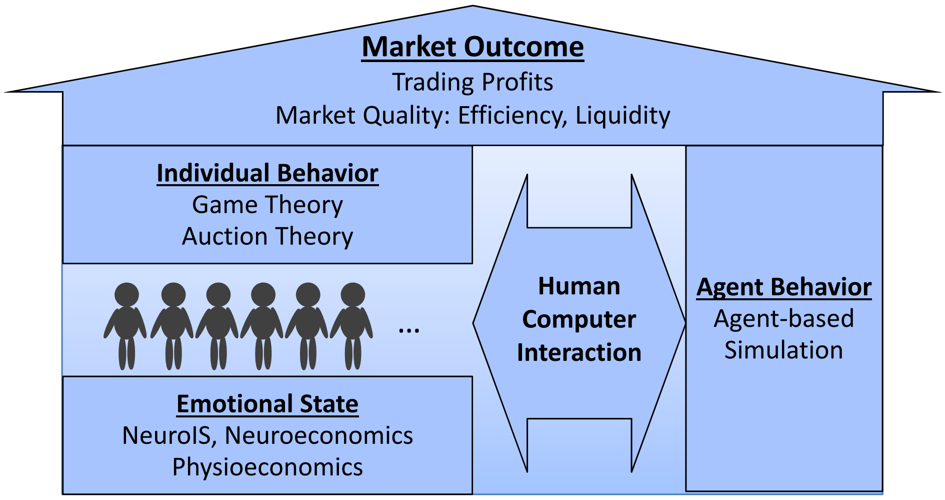


Figure 4.1: Market Framework for Human-Computer Interaction

Adam et al. (2011) 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, I assume that the interaction with 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. Luca et al., 2011; Riedl et al., 2011). Interaction of humans and computer interfaces is a subfield of the research area human-computer interaction (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. I distinguish between supportive computer systems and competitive computer agents that are sophisticated enough to overtake simple or even complex human tasks. The focus in this framework is on competitive market environments and, thus, I also concentrate on competitive computer agents.

Market outcome is depicted in the upper part of Figure 4.1. 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.

4.2.1 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, 2010). 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., 2011; Riedl et al., 2011). Dimoka et al. (2012) outline further research directions, some of them described below. In their recent work, Riedl et al. (2012) also address 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. (2011). A model for a more general emotion in competitive situations, "competitive arousal", is introduced by Ku et al. (2005). Adam et al. (2011) further introduce 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.

4.2.2 Application to IS Constructs

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.

In contrast to the supportive nature of agents, the research focus here is on 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) analyze 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) use 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 cause 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. I 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.

4.2.3 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 in 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. The framework is also embedded into this field. 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 and commodities. 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 demonstrates 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 conduct 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) are 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 and Bruten (1997b) 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" is 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) study 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 (Riordan and Storkenmaier, 2012; Zhang, 2013).

Implications for Market Design

In the experimental study, I 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 mechanism as used at professional stock exchanges. In order to simplify the market design and to ensure comprehensibility, I 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, I specifically concentrate on market efficiency in this 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, I apply NeuroIS tools in order to analyze human-computer interaction in the proposed competitive financial market setting. In order to gain statistically 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, I 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 this case study, I 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 this case, the expected inefficiency approaches to the one of an optimal mechanism with a precision of 0.0001 (cf. Rustichini et al., 1994). A market setting therefore requires a critical number of participants to provide a sufficient result regarding market efficiency. Thus, I 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. The application of more sophisticated tools, such as fMRI, would be highly desirable, but unrealistic to achieve at the current state of technology.

In order to ensure a competitive setting, I 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. I further introduce treatments for which I 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.

4.3 The Experiment

4.3.1 Experimental Design

The market design of this case study builds on the experiments of Smith (1962) and 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) define different market settings 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 this experiment, I distinguish between three different market settings, a symmetric market, a buyer market, and a seller market. Each session comprises all three market settings. Every market setting is played for 6 consecutive trading periods which each lasts 2.5 minutes by each trader.[1]

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, $i = 1,...,6$, which is drawn from the specified supply and demand functions. The values are randomized for each participant in order to avoid order biases. His or her trading profits for trading the ith unit are computed as $v_i - p_i$. The information about the (redemption) value of the $(i+1)$th is given to the buyer after the successful sell of the ith 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 the costs v_i for unit i, $i = 1,...,6$, and the trading profits for trading the ith unit is computed as $p_i - v_i$. The information about the redemption value of the $(i+1)$th unit is given to the seller after the successful buy of his or her ith 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.

All the above information in Section 4.3.1 is presented to the participants in the form of hard copy instructions as well as in an oral review of the instructions. The instructions can be found in Appendix B.1.

4.3.2 Participants and Incentives

The experiment was conducted at the IISM lab at Karlsruhe Institute of Technology. Following the induced value theory of Smith (1976), I directly link the actions of the participants to real monetary payoffs and conduct the experiment with university students with an academic background in economics. The participants were recruited from a pool of students using the ORSEE software environment (Greiner, 2004). A total of 288 students participated in the experiment with a male/female ratio of 77/23. No student took part in more than one experiment. Students have been frequently

[1] Moreover, subjects randomly participated in one of two abnormal market settings which are not reported here. The order of the market settings is randomized in order to control for learning effects and exhaustion.

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, I ask 8 comprehension questions beforehand in order to ensure comprehension of the market design. All participants have to answer all questions correctly in order for the experiment to begin. I further conduct 4 trial periods before the actual experiment so that the participants can get used to the user interface. Depending on their trading behavior in the experiment, the average payoff is approximately 25.00 Euros per participant. The minimum payoff was 10.00 Euros. The summary statistics are summarized in Table 4.1.

Table 4.1: Experiment Summary Statistics

	All	**HH**	**HAS**	**HAF**
Number of Cohorts	36	12	12	12
Number of Participants	288	144	72	72
Male/Female ratio	77/23			
Total Euros spent	6807.1			
Avg Euros per participant	23.64			

4.3.3 Treatment Structure and Procedure

The experiment comprises five treatments which are summarized in Table 4.2. 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. I account for this fact by introducing treatments in which half of the traders are represented by computer agents. Thus, in the HAS and the HAF 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. The agents vs. agents (AA) treatment only comprises computer agents.

I further distinguish between fast agents that have a sleep/wake cycle of 0.5 seconds +/- 50% (HAF and AAF) and slow agents which have a sleep/wake cycle of 5 seconds +/- 50% (HAS and AAS). 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-cohorts as well as between-subjects design, i.e. the cohorts / subjects exclusively participate in one of the 5 treatments. The subjects also keep their role as a buyer or a seller for the whole session. In order to measure physiological parameters, I introduce specific waiting times and an initial five minute rest period which is necessary for calibrating the physiological measurement for the individual participants. I used the bidders' average heart rate (HR) six to three seconds before they place a bid as a proxy for arousal. The HRs are normalized by the individual baseline HR measured during an initial five-minute resting period. Normalization makes HR comparable across the participants and treatments. Another important aspect is that the participants of the experiment are equipped with earmuffs to avoid susceptibility to background noise. Finally, the environmental conditions are kept as constant as possible and in the range of the recommended thresholds.

In order to control for heterogeneities in risk attitude, the subjects' individual risk attitudes and emotion regulation is assessed at the end of the experiment. The Holt and Laury questionnaire measures the level of risk aversion with real monetary payoffs (Holt and Laury, 2002). In this questionnaire, the subjects pick one of two lotteries with different levels of risk and expected payoffs ten times consecutively. The participant's attitude towards risk can be assessed based on how often a subject chooses the less risky lottery. For the analysis, I include the number of safe choices made by the subjects.

Emotion regulation (or emotion suppression) represents to which extent ER strategies are consciously applied by individual users. Therefore, the emotion regulation questionnaire (ERQ) by Gross and John (2003) is used, which focuses specifically on the strategies cognitive reappraisal and suppression. A factor analysis and validity checks on the measurement scale of the ERQ is conducted and a single measure for the strategy of emotion regulation, the ER score, is included in the analysis.

Table 4.2: Experimental Design

This table presents the design of the experiment. Data are drawn from 60 cohorts. Panel A presents the between-cohort treatment structure, Panel B presents the market period structure. The treatment structure has a factorial design of 3 × 2 for $Agent \times A_{fast}$: *Agent* represents the number of participating agents and A_{fast} is a dummy with 0 for slow agents and 1 for fast agents. The remainder of the 12 participants are represented by humans (indicated by *Human*). In order to ensure the robustness of results, the experiment is conducted for several cohorts (12 for each treatment) and for different 3 market settings with 6 trading periods each as depicted in Panel B. Market 1 is a symmetric market, market 2 is a seller market and market 3 is a buyer market.

Panel A: Treatment Structure

Treatment	Human	Agent	A_fast	Cohorts
HH	12	0	0	12
HAS	6	6	0	12
HAF	6	6	1	12
AAS	0	12	0	12
AAF	0	12	1	12

Panel B: Market Period Structure

Market	Period
1	1
1	2
1	3
1	4
1	5
1	6
2	1
2	2
2	3
2	4
2	5
2	6
3	1
3	2
3	3
3	4
3	5
3	6

4.3.4 Implementation

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

The trading interface is depicted in Figure 4.2. It 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 transaction history of the whole market.

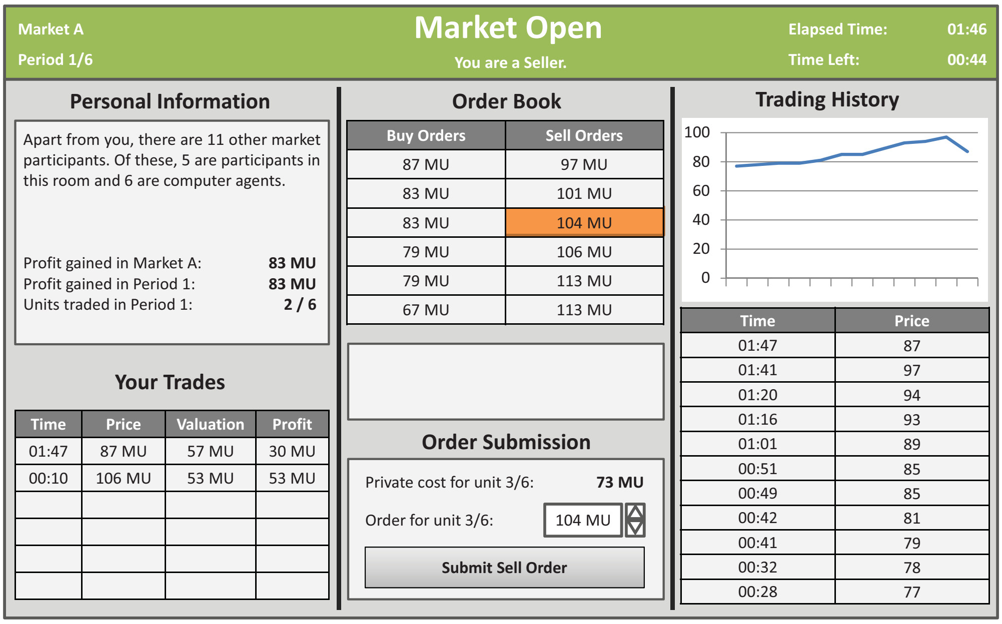


Figure 4.2: Trading Graphical User Interface

This figure shows the graphical user interface of the trading platform. 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.

Agent Implementation

ZIP agents were introduced by Cliff and Bruten (1997b) as an improvement over ZI agents in order to incorporate elementary aspects of machine learning into the algorithm. They introduce a profit margin which represents the relative difference of a trader's reservation price and the corresponding trade price and is used to determine a ZIP agent's quote. It is defined as $p_i = \lambda_{i,j}(1 + \mu_i)$ where p_i is the current quote of ZIP Agent Trader i, $\lambda_{i,j}$ the j-th reservation price of trader i, and μ_i the profit margin of trader i. ZIP agents adjust their profit margin based on order book information (i.e. latest quotes - bids and asks from other traders) and trade prices. When to adjust the ZIP Agent Trader's profit margin is determined by the latest quote in the following aspects: if it was a bid or an ask, if it led to orders being matched (a trade), and if it was greater or less than the ZIP agent's current quote.

From these aspects, a ZIP **seller** *increases* its profit margin if the latest quote led to a trade and the latest quote was higher than his own current quote. He *decreases* his profit margin if the latest quote was an ask and lower than the ZIP seller's current quote, or if the latest quote was a bid which led to a trade and which was lower than the ZIP agent's current quote.

Adjusted accordingly, the same applies for ZIP **buyers**. This means, a ZIP buyer *increases* its profit margin if the latest quote led to a trade and the latest quote was lower than the ZIP Agent Trader's current quote. He *decreases* his profit margin if the latest quote was a bid and higher than the ZIP buyer's current quote, or if the latest quote was a bid which led to a trade and which was higher than the ZIP Agent Trader's current quote. A detailed pseudo-code can be found in Figure 4.3.

Adaptive rules for the ZIP seller
- if(last shout was accepted at price q)
- then
1. any seller j for which $p_i \leq q$ should raise its profit margin
2. if(last shout was a bid) then
a) any active seller s_i for which $p_i \geq a$ should lower its profit margin
- else
1. if(last shout was an offer)
then
a) any active seller s_i for which $p_i \geq q$ should lower its profit margin

Adaptive rules for the ZIP buyer
- if(last shout was accepted at price q)
- then
1. any buyer b_i for which $p_i \geq q$ should raise its profit margin
2. if(last shout was a bid)
a) any active buyer b_i for which $p_i \leq q$ should lower its profit margin
- else
1. if(last shout was a bid)
a) any active buyer b_i for which $p_i \leq q$ should lower its profit margin

Figure 4.3: Pseudo-Code for ZIP agents
Pseudo-Code as in Cliff and Bruten (1997a, p.43)

4.4 Statistical Analysis

For the analysis of the different treatments, I use a fixed effects model as well as a moderator-mediator analysis in order to analyze direct, moderated and mediated effects on the individual trader level as well as on a market-period level.

4.4.1 Individual Trader Analysis

Due to significant fixed effects for different market settings and trading periods, I apply a fixed effects model on the individual trader level. I test the different treatments separately, i.e. I introduce a dummy variable for both the HAS and the HAF treatment. The baseline for each regression model is the HH treatment. As fixed effects, I include *Period* fixed effects for periods 1 to 6 as well as for the *Marketrole*, i.e. being a buyer / seller in each of the 3 market settings (symmetric, buyer, seller). $Mrole_r, r = 1, ..., 6$ represents 6 dummy variables, one for each of the 2 roles (buyer, seller) in each of the 3 market settings. I estimate the following equation on an individual trader level:

$$\begin{aligned} Y_{r,s,i} = {} & Intercept + \alpha * HAS + \beta * HAF + \sum_{r=1}^{6} \gamma_r * Mrole_r \\ & + \sum_{s=1}^{6} \delta_s * Period_s + Control_i + \epsilon_{r,s} \end{aligned} \tag{4.1}$$

The *Intercept* represents the average for the *HH* treatment in period 6 for a buyer in the symmetric market. As *Control*, I include the risk aversion (proxied by the number of safe choices) and emotion regulation score of every participant. Trading behavior variables comprise emotional arousal as well as trading and pricing aggressiveness.

I apply the fixed effects model above to analyze the direct treatment effects on trading behavior and emotional arousal which are depicted as red arrows in Figure 4.4, Model 1a below. In order to assess the conditional indirect effect of arousal on aggressiveness, i.e. the orange arrow, I conduct a mediator analysis and a bootstrapping analysis based on 500 bootstrapped samples using 95% confidence intervals.

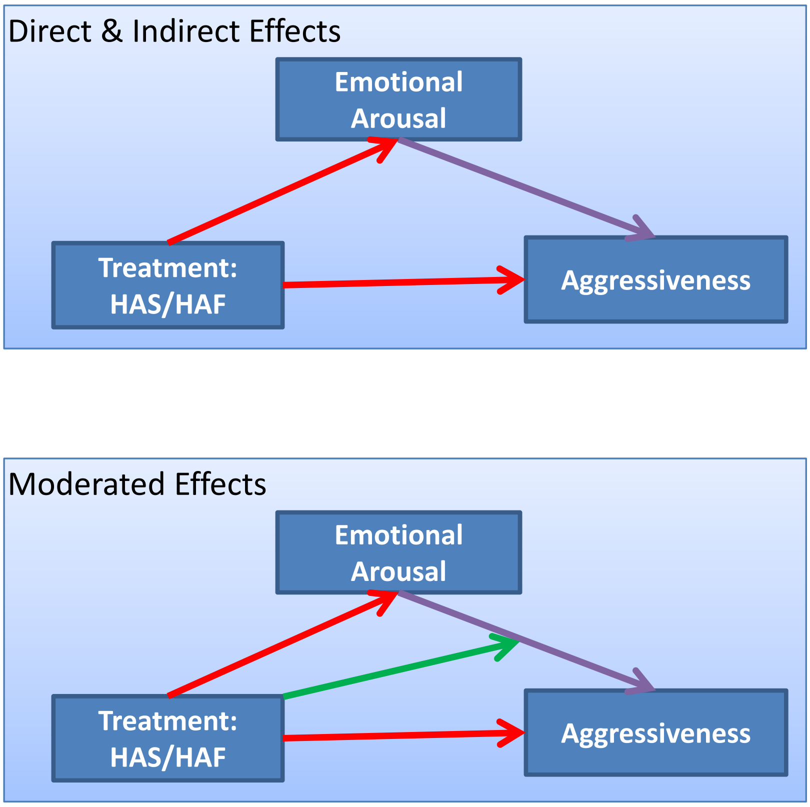


Figure 4.4: Direct and Indirect Effects on Trading Behavior: Model 1a and Model 1b

4.4.2 Market Level Analysis

I estimate a similar following fixed effects regression on a market-period level:

$$\begin{aligned} X_{r,s} = {} & Intercept + \alpha * HAS + \beta * HAF + \sum_{r=1}^{3} \gamma_r * Market_r \\ & + \sum_{s=1}^{6} \delta_s * Period_s + \epsilon_{r,s} \end{aligned} \tag{4.2}$$

While the dummy variables HAS and HAF and *Period* fixed effects are identically defined as above, I include $Market_r$ fixed effects for different market settings (symmetric, buyer, seller). The *Intercept* represents the average for the *HH* treatment in period 6 for the symmetric market. The market-period level analyses focus on allocative efficiency, liquidity, and profit dispersion measures.

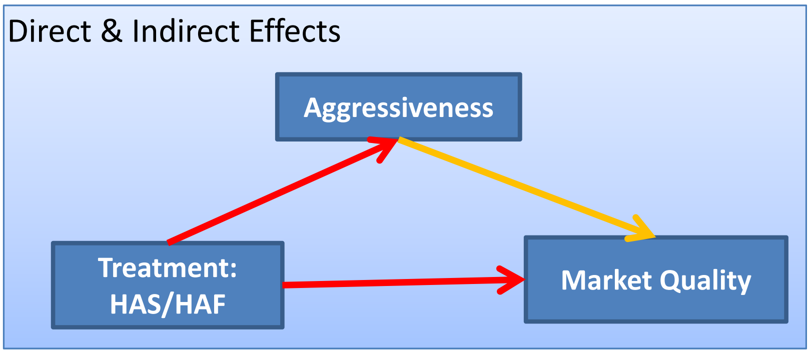


Figure 4.5: Direct and Indirect Effects on Market Quality: Model 2

4.5 Results

The results are divided into three parts: Firstly, I discuss the effects on emotional arousal. Secondly, the influence of different treatments and the mediating and moderating effects of treatment and arousal on trading behavior are analyzed. Finally, I test direct and mediated effects on trading behavior and market quality in terms of efficiency and liquidity.

4.5.1 Effects on Emotional Arousal

To measure the emotional state of the human traders, I measure the heart rate of each participant as the overall level of emotional arousal. I compute the average heart rate for each human trading participant by market and trading period and analyze the heart rate over time. Results are presented in Figure 4.6.

Figure 4.6 shows the average heart rate for the participants, averaged over a trading period and subtracted by the individual baseline HR measured during an initial five-minute resting period. It is shown that the level of the heart rate is highest in the first 10 seconds of the trading period. Since most of the market activity occurs during the first 10 seconds, the analyses that include the heart rate focus on the first 10 seconds.

I conduct the fixed effects regressions with heart rate measures to measure the direct treatment effects on heart rate. Results are reported in Table 4.3. The estimates of the first regression in Panel A show overall differences in the level of arousal. There are different competing effects of computer agents and agent speed on the emotional arousal of participants. The HAF treatment induces a significantly higher level of arousal than the baseline, the HH treatment, which stems from the increased trading speed and "time pressure". Interestingly, the HAS treatment depicts a significantly lower level of arousal.

The results on emotional arousal can be further discussed in the context of the psychological theory on "competitive arousal". In psychology literature, the construct of competitive arousal is related to risk taking behavior. Ku et al. (2005) demonstrates that competition against other human traders induces a high level of competitive arousal as well as higher risk taking behavior. On the other side, the increasing speed of trading agents also induces a certain "time pressure". When introducing fast agents, the number of market events within a time period increases and the convergence towards the equilibrium becomes faster. Therefore, humans must act faster in order to gain profits. This in turn induces a higher level of time pressure which then translates into higher arousal and higher risk taking. Therefore, I hypothesize that there are opposing effects caused by trading agents, such as the effect of "de-emotionalization", i.e. the lack of competitiveness towards trading agents, and the effect of time pressure caused by the presence of fast agents. The experimental results strengthen the hypothesis of de-emotionalization by slow computer agents, reflected by a lower heart rate. The decreasing effect is also comparably higher than the increasing time pressure effect by fast agents on arousal. In order to gain more detailed insight into the effects on actual trading behavior, I further link the results on emotional arousal to behavioral measures of aggressiveness, specifically price and trade aggressiveness.

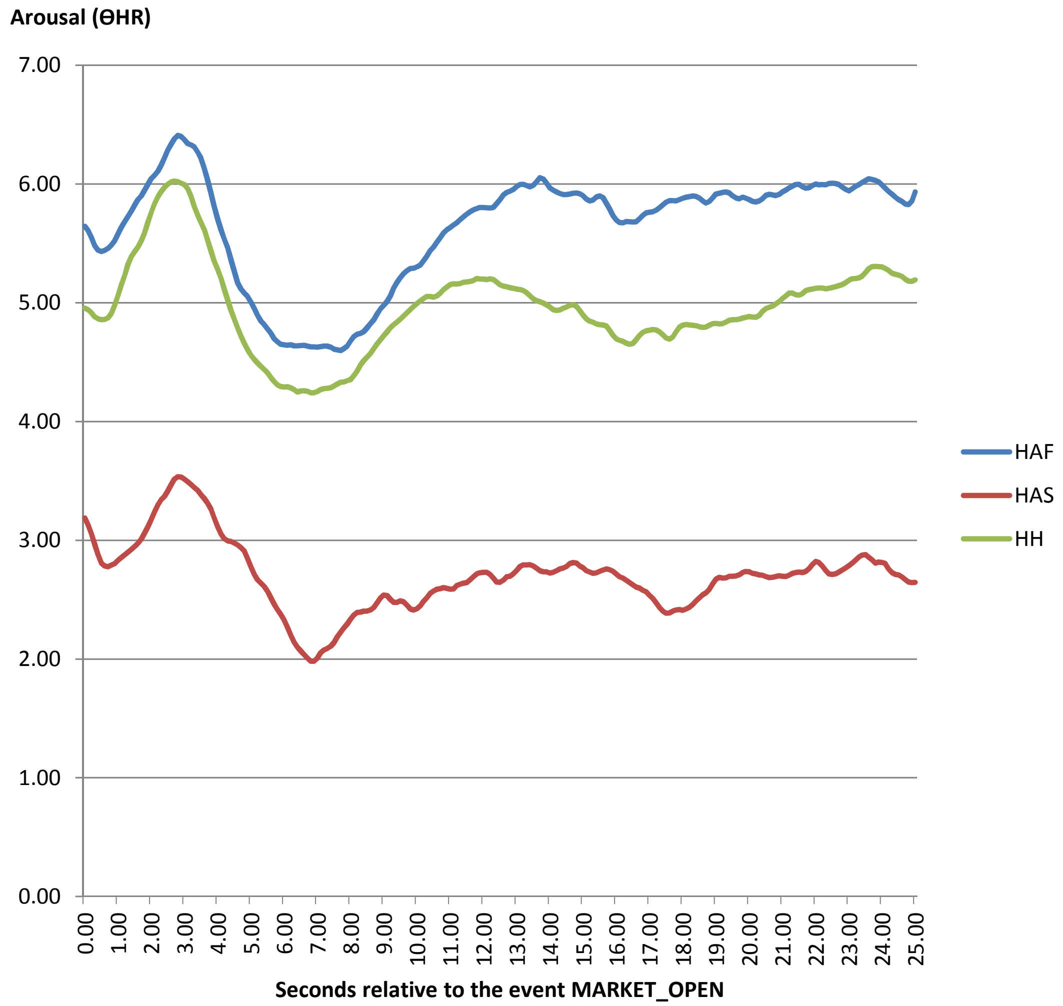


Figure 4.6: Heart Rate for different Treatments

This figure presents the heart rate of human traders for different treatments during the first 25 seconds of the trading period. The measures are computed as averages on an individual trader level.

Table 4.3: Direct and Indirect Effects on Price Aggressiveness
This table presents regression estimates on arousal measured by heart rate (HR) and price aggressiveness according to Model 1a in Figure 4.4. Panel A depicts three regression on HR and price aggressiveness with the independent treatment variables HAS, HAF, and HR and control variables risk aversion (Riskav) and emotion regulation (ER). Panel B further presents bootstrapping results and 95% confidence intervals of the indirect effects of the HAS and HAF treatment.

Panel A: Direct and Indirect Effects						
Dep. Variable	HR		Priceaggr		Priceaggr	
	Estimate	p-val	Estimate	p-val	Estimate	p-val
Intercept	6.072	0.00	1.300	0.00	1.295	0.00
HAS	-2.349	0.00	0.094	0.00	0.096	0.00
HAF	1.515	0.00	-0.037	0.10	-0.038	0.10
HR					0.001	0.40
Controls						
Riskav	-2.365	0.11	-0.071	0.41	-0.067	0.43
ER	1.065	0.00	0.004	0.68	0.003	0.75
Panel B: Confidence Interval for Indirect Effect						
	Mean	Std	Stderror	Lower	Upper	
HAS	-0.0020	0.0024	0.0001	-0.0070	0.0026	
HAF	0.0004	0.0008	0.0000	-0.0008	0.0021	

4.5.2 Trading Behavior

In the analysis on trading behavior, I distinguish between aggressiveness measures of pricing and trading behavior of participants.

Price Aggressiveness

Price aggressiveness is measured by the log-ratio of potential profit and theoretical profit that can be realized with submitted orders. Specifically, I compute the theoretical profit $\pi_{i,j}$ for unit i and trader j and the "potentially" realized profit is computed as the difference of the submitted limit order price $l_{i,j}$ and the assigned private value $v_{i,j}$: $b_{i,j}=l_{i,j} - v_{i,j}$. This potential profit is computed as $log(b_{i,j}/\pi_{i,j})$. The lower the potential profit, the higher the price aggressiveness since in this market setting, higher price aggressiveness represents a lower willingness to risk not being executed and a higher willingness to forgo profit that could theoretically be realized than not being executed. Thus, the lower the regression estimates on price aggressiveness are, the higher the price aggressiveness of participants. The results are presented in Table 4.3 above.

In Regression 2 of Panel A in Table 4.3, there is a significantly positive treatment effect of HAS on price aggressiveness, while HAF has a negative effect. The latter is consistent with the "time pressure" effect which causes human participants to submit orders closer to their private value, i.e. quote more aggressively, than if not under time pressure. Thus, these findings strengthen the effect of time pressure in the context of competitive arousal. As for the presence of slow agents, these would rather have the above mentioned "de-emotionalization" effect and thus lead to decreased aggressiveness.

However, there is no significant indirect effect of arousal on time pressure as shown by the estimates in Regression 3 in Panel A. Thus, the time pressure effect on price aggressiveness is independent from the actual normalized level of heart rate. I further analyze moderating effects of human versus human competition as well as emotion regulation effects which significantly influences the heart rate level of participants. Results are shown in Table 4.4.

Table 4.4: Moderated Effects on Price Aggressiveness

This table presents the results on moderated effects of heart rate (HR) on price aggressiveness according to Model 1b in Figure 4.4. The HH treatment (representing human vs. human competition) and emotion regulation (ER) serve as moderators for the arousal effect on price aggressiveness. Control variables risk aversion (Riskav) and emotion regulation (ER) are further applied. Panel B presents bootstrapping results for moderating effects of HH and ER.

Panel A: Moderated Effects on Price Aggressiveness					
	HH Moderation		HH/ER Mod		
	Estimate	p-val	Estimate	p-val	
Intercept	1.300	0.00	1.299	0.00	
HAS	0.087	0.00	0.099	0.00	
HAF	-0.048	0.05	-0.037	0.11	
HR	0.002	0.18	0.001	0.40	
HR*HH	-0.002	0.29			
HR*ER*HH			0.003	0.03	
Controls					
Riskav	-0.066	0.44	-0.081	0.34	
ER	0.003	0.77	-0.007	0.58	
Panel B: Confidence Interval for Moderated Effect					
	Mean	Std	Stderror	Lower	Upper
HR+HR*HH	-0.0002	0.0012	0.0001	-0.0026	0.0022
HR+HR*ER*HH	0.0041	0.0017	0.0001	0.0007	0.0074

While there is no significant moderating effect of the HH treatment alone (HR*HH), there is in fact one for participants with high ER scores (HR*ER*HH). Emotion regulation plays a major role for decision making. It has been shown that traders and investors with high emotion regulation capabilities perform better in trading (Fenton-O'Creevy et al., 2012). As shown here, participants with a high ER score are more prone to effects of heart rate on their pricing behavior which indicates a higher level of competitiveness between this kind of participants. I further analyze another measure for aggressiveness, trade aggressiveness, which measures the immediateness of trade executions that are intended by the participants.

Trade Aggressiveness

Trade aggressiveness is measured by the ratio of initiated trades to the number of total trades by a trader. A trade is initiated by a the submission of a marketable order which is executed against a passive order in the order book. Higher liquidity demand in general market settings represents a lower willingness to wait for being executed and a higher willingness to pay for immediacy. In this market setting, it can also be interpreted as a lower willingness to risk the execution of the order and to "wait" for higher profits using a passive limit order. In market microstructure literature, the measure of relative liquidity demand is often interpreted as trading aggressiveness. In the behavioral context, higher trading aggressiveness is related to lower risk taking since trading aggressively also means to rather forego profit and trade right away than risk the possibility of not getting executed. The possibility of achieving higher profits thus points in the opposite direction of the "execution risk". I argue that in this market setting, "execution risk" is more relevant for a profit optimizing strategy since the convergence towards the equilibrium price can be observed and learned very quickly and is therefore close to deterministic. The results for direct and indirect treatment effects on trade aggressiveness are presented in Table 4.5.

As depicted in Table 4.5, the presence of fast trading agents in treatment HAF again induces higher aggressiveness similarly to the results on price aggressiveness. Interestingly, the HAS treatment leads to significantly higher trade aggressiveness as well. Since the effects of HAS and HAF both point into the same direction, this might allow inference of overall effects of de-emotionalization by agents. However, trade aggressiveness allows a less nuanced study than price aggressiveness, which takes the actual submitted limit prices into account. Additionally, the results are also mechanically driven since agent strategies are by nature more aggressive in terms of their choice of a marketable or non-marketable order. This in turn then leads to higher trade aggressiveness of human participants. These differences have to be taken into account before making inferences based on trade aggressiveness.

Similar to the results on price aggressiveness, the indirect effects of arousal on trade aggressiveness are weak. Since emotion regulation has a significant direct effect on

Table 4.5: Direct and Indirect Effects on Trade Aggressiveness
This table presents regression estimates on arousal measured by heart rate (HR) and trade aggressiveness according to Model 1a in Figure 4.4. Panel A depicts three regression on HR and trade aggressiveness with the independent treatment variables HAS, HAF, and HR and control variables risk aversion (Riskav) and emotion regulation (ER). Panel B further presents bootstrapping results and 95% confidence intervals of the indirect effects of treatments HAS and HAF.

Panel A: Direct and Indirect Effects						
Dep. Variable	HR		Tradeaggr		Tradeaggr	
	Estimate	p-val	Estimate	p-val	Estimate	p-val
Intercept	6.072	0.00	0.528	0.00	0.529	0.00
HAS	-2.349	0.00	0.050	0.00	0.049	0.00
HAF	1.515	0.00	0.027	0.04	0.027	0.04
Arousal					0.000	0.79
Controls						
Riskav	-2.365	0.11	-0.005	0.92	-0.005	0.92
ER	1.065	0.00	-0.016	0.01	-0.016	0.01
Panel B: Confidence Interval for Indirect Effect						
	Mean	Std	Stderror	Lower	Upper	
HAS	0.0004	0.0012	0.0001	-0.0018	0.0028	
HAF	-0.0003	0.0008	0.0000	-0.0018	0.0011	

trade aggressiveness and played an important moderating role for price aggressiveness, I further analyze the moderating effects of the HH treatment and emotion regulation capacity. The results show insignificant moderating effects of the HH treatment and the emotion regulation on the effect of emotional arousal on trade aggressiveness.

Based on the results on price aggressiveness, it can be inferred that emotional arousal plays a role in the HH treatment due to the competition effect between human traders. This effect is mostly prominent for participants with higher ER scores. However, it is eased by the presence of agents due to a "de-emotionalization" effect, and specifically by fast agents which create a contrary time pressure effect. These findings are in line with previous literature on competitive arousal which focuses on diverse factors such as rivalry, social facilitation and time pressure among others, but solely restricted to human-human interaction. In the presence of agents however, speed, and thus "time pressure", plays a more vital role than competitiveness.

Table 4.6: Moderated Effects on Trade Aggressiveness
This table presents the results on moderated effects of heart rate (HR) on trade aggressiveness according to Model 1b in Figure 4.4. The HH treatment (representing human vs. human competition) and emotion regulation (ER) serve as moderators for the arousal effect on trade aggressiveness. Control variables risk aversion (Riskav) and emotion regulation (ER) are further applied. Panel B presents bootstrapping results for moderating effects of HH and ER.

Panel A: Moderated Effects on Trade Aggressiveness					
	HH Moderation		HH/ER Mod		
	Estimate	p-val	Estimate	p-val	
Intercept	0.529	0.00	0.527	0.00	
HAS	0.049	0.00	0.049	0.00	
HAF	0.026	0.07	0.027	0.04	
Arousal	0.000	0.93	0.000	0.77	
Arousal*HH	0.000	0.86			
Arousal*ER*HH			-0.001	0.24	
Controls					
Riskav	-0.005	0.92	0.000	1.00	
ER	-0.016	0.01	-0.013	0.07	
Panel B: Confidence Interval for Moderated Effect					
	Mean	Std	Stderror	Lower	Upper
HR+HR*HH	-0.0002	0.0007	0.0000	-0.0016	0.0011
HR+HR*ER*HH	-0.0013	0.0010	0.0000	-0.0035	0.0007

4.5.3 Market Quality

Market quality is measured specifically by allocative efficiency, profit dispersion, market volume, spreads, and depth.

Allocative Efficiency

In order to measure market quality, I use the variable $Alpha$ which is used by Smith (1962). $Alpha$ is defined as the standard deviation σ_i of trade prices around the equilibrium price P_i relative to the equilibrium price: $\alpha = 100 * \sigma_i / P_i$. The higher $Alpha$, the higher the price variation around the equilibrium price, and the less efficient trade prices. Figure 4.7 presents efficiency results over time for the different treatments.

As shown in Figure 4.7, market efficiency increases over time and that efficiency increases with an increasing number of computer agents as well. In order to check for further robustness, I also present results by different market settings (symmetric, seller, and buyer) and trading periods in Figure 4.8 and also find consistent results.

For a more robust analysis, the fixed effects regression results are presented in Table 4.7. The results of Regression 2 in Panel A show that both HAS and HAF increase efficiency by decreasing alpha, although only the decrease of HAF is efficient. It thus shows how the presence of slow agents increase market efficiency. Faster agents moreover introduce an increased time pressure. It should be noted however that this increase in market speed mechanically leads to a faster conversion of trade prices to the equilibrium price.

To get an idea of the role of price aggressiveness for efficiency, I further analyze the indirect effects. These show that price explains a large amount of variation in the alpha measure, primarily in the HAS treatment however. The bootstrapping result confirm this finding. This indicates that the introduction of time pressure in the HAF treatment has a direct effect on efficiency while changes in order pricing behavior lead to the positive effects on efficiency in the HAS treatment.

Table 4.7: Direct and Indirect Effects on Market Efficiency
This table presents regression estimates on allocative efficiency, measured by alpha, and price and trade aggressiveness according to Model 2 in Figure 4.5. Panel A1 / A2 depicts three regression on alpha and price and trade aggressiveness respectively with the independent treatment variables HAS, HAF, and HR. Panel B1 / B2 further presents bootstrapping results and 95% confidence intervals of the indirect effects of the HAS and HAF treatment.

Panel A1: Direct and Indirect Effects						
Dep. Variable	Priceaggr		Alpha		Alpha	
	Estimate	p-val	Estimate	p-val	Estimate	p-val
Intercept	1.036	0.00	3.441	0.00	0.062	0.91
HAS	0.066	0.01	-0.175	0.53	-0.389	0.15
HAF	-0.028	0.27	-0.593	0.04	-0.501	0.06
Priceaggr					3.261	0.00
Panel B1: Confidence Interval for Indirect Effect						
	Mean	Std	Stderror	Lower	Upper	
HAS	0.2146	0.0846	0.0038	0.0777	0.3904	
HAF	-0.0939	0.0809	0.0036	-0.2460	0.0614	
Panel A2: Direct and Indirect Effects						
Dep. Variable	Actpass		Alpha		Alpha	
	Estimate	p-val	Estimate	p-val	Estimate	p-val
Intercept	0.010	0.00	3.441	0.00	3.276	0.00
HAS	0.008	0.00	-0.175	0.53	-0.190	0.51
HAF	0.008	0.00	-0.593	0.04	-0.602	0.03
Actpass					0.327	0.82
Panel B2: Confidence Interval for Indirect Effect						
	Mean	Std	Stderror	Lower	Upper	
HAS	0.0186	0.0662	0.0030	-0.1065	0.1572	
HAF	0.0117	0.0380	0.0017	-0.0607	0.0958	

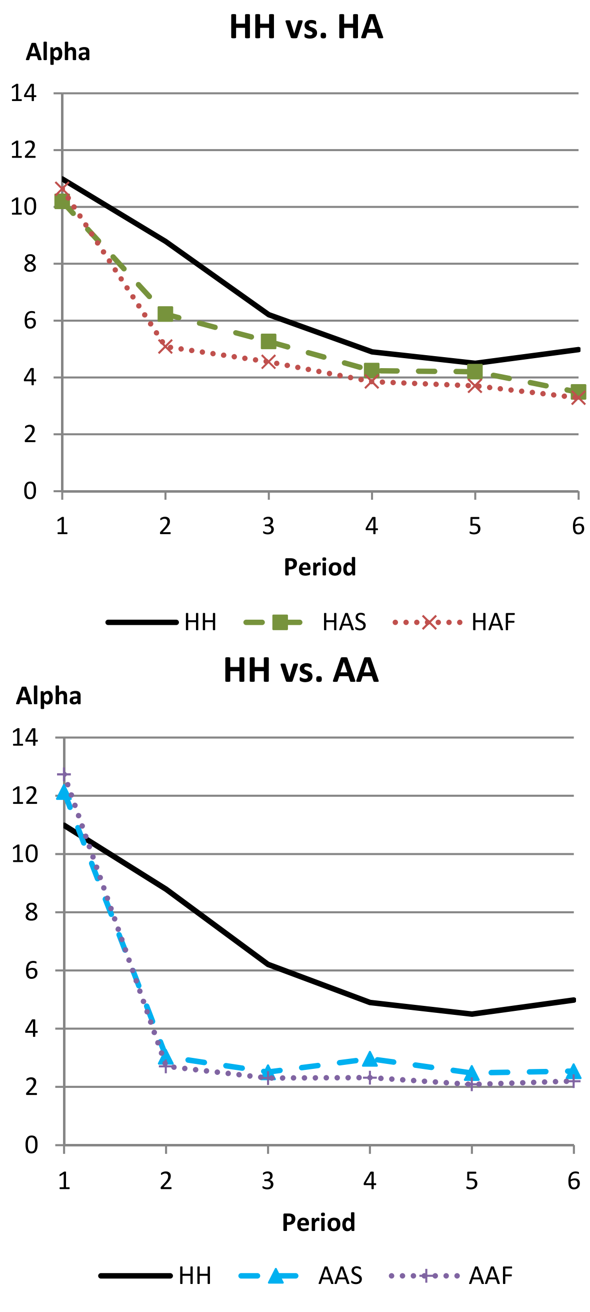


Figure 4.7: Alpha for different Treatments
This set of figures presents the $Alpha$ values for the different treatments HH, HAS, and HAF over the 6 trading periods. The measures are computed as averages on a marketperiod-level.

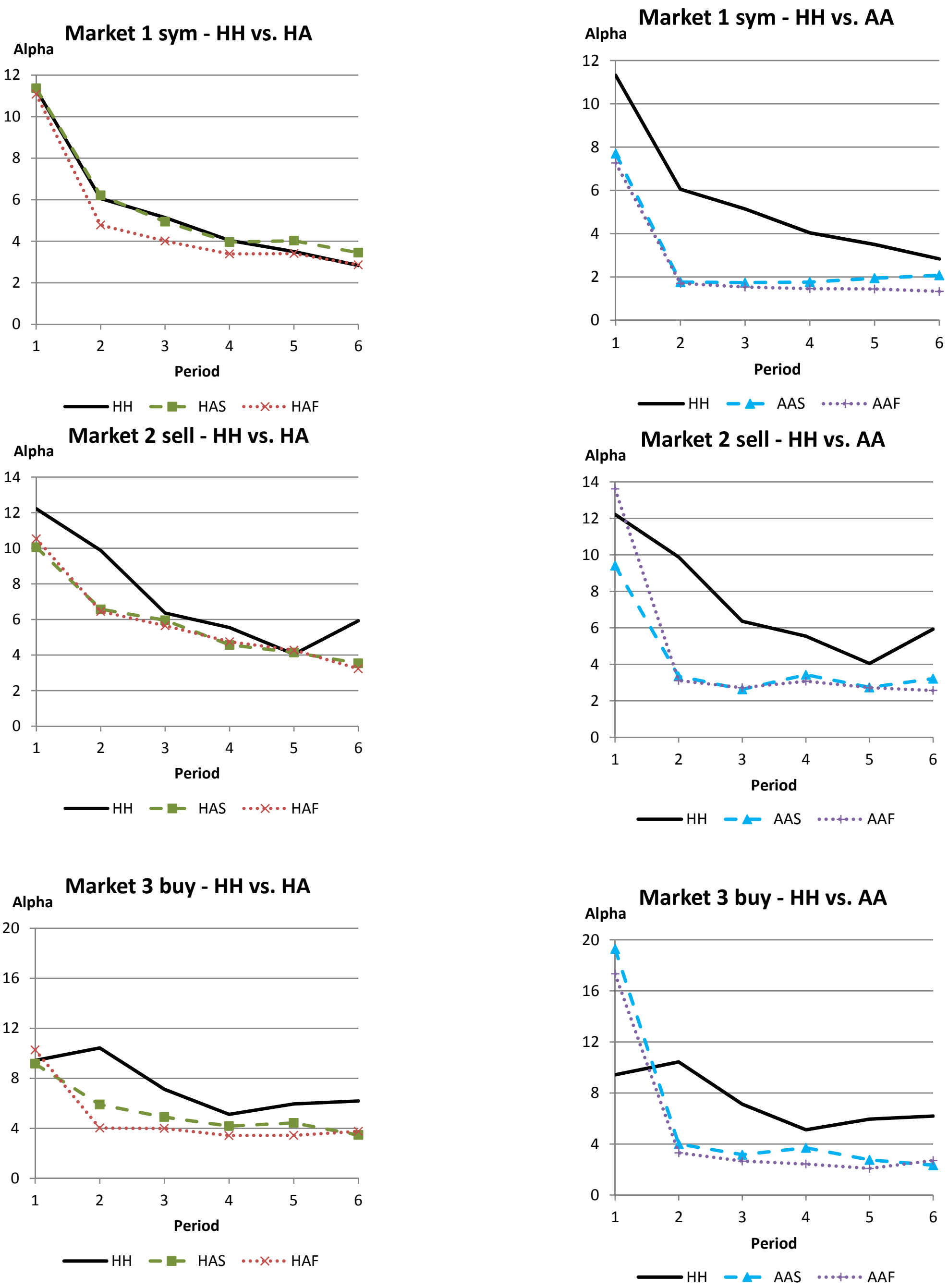


Figure 4.8: Alpha for different Treatments and Market Settings
This set of figures presents the $Alpha$ values for the different treatments HH, HAS, and HAF over the 6 trading periods and for the different market settings. The measures are computed as averages on a marketperiod-level.

Profit Dispersion

Trading profits are measured as the ratio of realized profit $a_j = \sum_{i,j} v_{i,j} - p_{i,j}$ and the theoretical equilibrium profits π_j, i.e. the difference between assignment and equilibrium price, for each trader j: a_j/π_j. Profit dispersion is computed as the root mean squared difference between the transaction price and the assignment value: $\sqrt{1/n * \sum_j (a_j - \pi_j)^2}$ with a_j being the actual profits and π_j the theoretical equilibrium profits of each trader j for all his n transactions.

Figure 4.9 presents average profit dispersion over the trading period for different treatments. There is a monotonous decrease of trading profit dispersion over the trading periods. HH is the treatment with the highest trading profit dispersion and HAF the treatment with the lowest trading profit dispersion. Thus, profit dispersion decreases with the presence of agents. In order to distinguish between the dispersion of human and agent profits, I further compute the results for only human profits. I observe that human profit dispersion increases for the HA effect, so the previously observed decrease actually stems from the agent profit distribution. I thus conclude that the distributional aspects of market performance actually improve for agents, but worsen for human traders in mixed markets with slow agents.

I further analyze the impact of price and trade aggressiveness on profit dispersion. Results are presented in Table 4.8. From these results, a weak positive indirect effect of price aggressiveness on profit dispersion can be inferred. However, the analysis of moderated effects show that the effect is primarily present for the HAS treatment and is significant on a 5 % level in that case. There is no significant effect from trade aggressiveness.

It can be inferred that the link between price aggressiveness and profit dispersion is strong in the HAS treatment due to the lack of time pressure. Thus, time pressure would directly lead to a higher profit dispersion, while HAS leads to lower aggressiveness and thus lower profit dispersion.

Table 4.8: Direct and Indirect Effects on Profit Dispersion
This table presents regression estimates on profit dispersion and price and trade aggressiveness according to Model 2 in Figure 4.5. Panel A1 / A2 depicts three regression on profit dispersion and price and trade aggressiveness respectively with the independent treatment variables HAS, HAF, and HR. Panel B1 / B2 further presents bootstrapping results and 95% confidence intervals of the indirect effects of treatments HAS and HAF.

Panel A1: Direct and Indirect Effects						
Dep. Variable	Priceaggr		Profitdisp		Profitdisp	
	Estimate	p-val	Estimate	p-val	Estimate	p-val
Intercept	0.033	0.00	10.296	0.00	1.391	0.41
HAS	0.026	0.01	-0.139	0.87	-0.703	0.40
HAF	0.026	0.27	-0.901	0.29	-0.658	0.42
Priceaggr					8.595	0.00
Panel B1: Confidence Interval for Indirect Effect						
	Mean	Std	Stderror	Lower	Upper	
HAS	0.5689	0.2305	0.0103	0.1841	1.0520	
HAF	-0.2510	0.2187	0.0098	-0.6716	0.1633	
Panel A2: Direct and Indirect Effects						
Dep. Variable	Actpass		Profitdisp		Profitdisp	
	Estimate	p-val	Estimate	p-val	Estimate	p-val
Intercept	0.010	0.00	10.296	0.00	10.127	0.00
HAS	0.008	0.00	-0.139	0.87	-0.154	0.86
HAF	0.008	0.00	-0.901	0.29	-0.910	0.29
Actpass					0.334	0.94
Panel B2: Confidence Interval for Indirect Effect						
	Mean	Std	Stderror	Lower	Upper	
HAS	0.0280	0.2008	0.0090	-0.3554	0.4554	
HAF	0.0188	0.1146	0.0051	-0.1960	0.2816	

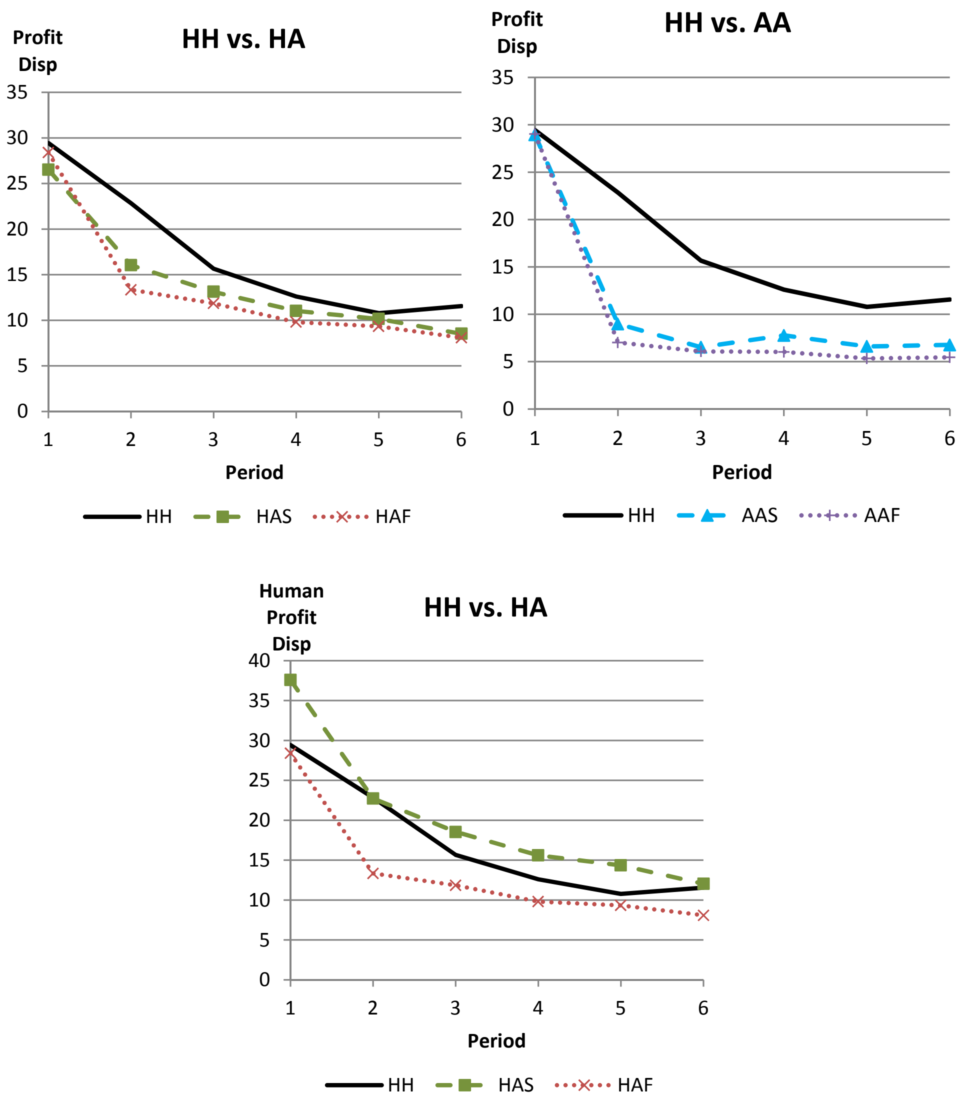


Figure 4.9: Profit Dispersion for different Treatments
This set of figures presents the profit dispersion of human traders for the different treatments HH, HAS, HAF, AAS, and AAF over the 6 trading periods. The measures are computed as averages on an individual trader level for each treatment and trading period.

Table 4.9: Direct and Indirect Effects on Human Profit Dispersion
This table presents the regressions on human profit dispersion and price and trade aggressiveness according to Model 2 in Figure 4.5. Panel A1 / A2 depicts three regression on profit dispersion and price and trade aggressiveness respectively with the independent treatment variables HAS, HAF, and HR. Panel B1 / B2 further presents bootstrapping results and 95% confidence intervals of the indirect effects of treatments HAS and HAF.

Panel A1: Direct and Indirect Effects						
Dep. Variable	Priceaggr		Profitdisp_h		Profitdisp_h	
	Estimate	p-val	Estimate	p-val	Estimate	p-val
Intercept	0.033	0.00	9.277	0.00	-2.371	0.28
HAS	0.026	0.01	5.790	0.00	5.053	0.00
HAF	0.026	0.27	4.771	0.00	5.088	0.00
Priceaggr					11.243	0.00
Panel B1: Confidence Interval for Indirect Effect						
	Mean	Std	Stderror	Lower	Upper	
HAS	0.7457	0.3068	0.0137	0.2328	1.3921	
HAF	-0.3268	0.2847	0.0127	-0.8876	0.2150	
Panel A2: Direct and Indirect Effects						
Dep. Variable	Actpass		Profitdisp_h		Profitdisp_h	
	Estimate	p-val	Estimate	p-val	Estimate	p-val
Intercept	0.010	0.00	9.277	0.00	8.682	0.01
HAS	0.008	0.00	5.790	0.00	5.737	0.00
HAF	0.008	0.00	4.771	0.00	4.740	0.00
Actpass					1.182	0.83
Panel B2: Confidence Interval for Indirect Effect						
	Mean	Std	Stderror	Lower	Upper	
HAS	0.0732	0.2829	0.0127	-0.4679	0.6621	
HAF	0.0462	0.1623	0.0073	-0.2605	0.4009	

Market Volume, Spreads, and Depth

I further study market liquidity in the dimensions market volume, bid-ask spreads, and depth. Market *Volume* is defined as the absolute number of units traded within the market-period and represents the overall trading activity on the market. *Spread* is computed as the average spread of the best bid and best ask price over the mid-point $mid = (ask + bid)/2$: $Spread = (ask - bid)/mid * 100$. Lower spreads can be interpreted as lower transaction costs for trading and thus higher liquidity. *Depth* represents the number of orders submitted to both the buy (bid) and sell (ask) side of the limit order book: $Depth = (count_{ask} + count_{bid})/2$. Higher depth can be interpreted as higher liquidity.

Figure 4.10 presents the results by market setting and trading period. Volume results are consistent for all three market settings in terms of an increase with the number of active agents in the market. The spreads similarly decrease, which equates to higher liquidity in the presence of agents. Depth however does not exhibit this improvement in liquidity as the other variables.

In order to have a deeper understanding between price and trade aggressiveness and the different market quality measures in the market, I apply the statistical analysis as depicted in Model 2 in Figure 4.5 to the three measures of market quality volume, spreads, and depth. The results in Table 4.10 show a strong increasing effect of price aggressiveness on market spreads, specifically in the HAS treatment, which can be interpreted that lower aggressiveness decreases liquidity. This result however is partly mechanical since the spread is computed as the difference between quoted bid and ask prices.

However, trade aggressiveness shows a consistently negative influence of trade aggressiveness on spreads for both the HAS and the HAF treatment. This is in line with previous microstructure literature on trade aggressiveness where it is equated with liquidity demand. Thus, the finding here provide experimental confirmation of this interpretation of the relationship between trade aggressiveness and spreads.

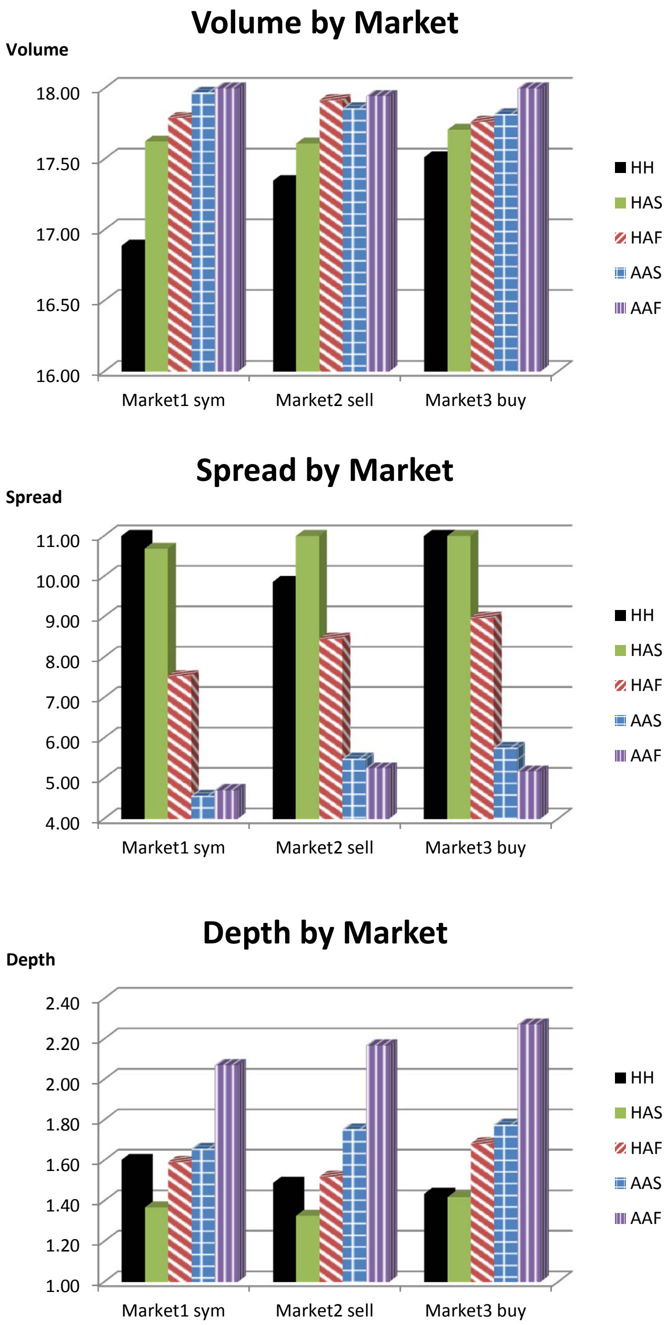


Figure 4.10: Market Quality for different Market Settings

In this set of figures, I present averages of market quality measures for the treatments *HH*, *HAS*, *HAF*, *AAS*, and *AAF* for different market settings. The measures are computed as averages for each treatment and market setting.

Table 4.10: Direct and Indirect Effects on Spreads

This table presents regression estimates on quoted spread and price and trade aggressiveness according to Model 2 in Figure 4.5. Panel A1 / A2 depicts three regression on spread and price and trade aggressiveness respectively with the independent treatment variables HAS, HAF, and HR. Panel B1 / B2 further presents bootstrapping results and 95% confidence intervals of the indirect effects of the HAS and HAF treatment.

Panel A1: Direct and Indirect Effects						
Dep. Variable	Priceaggr		Spread		Spread	
	Estimate	p-val	Estimate	p-val	Estimate	p-val
Intercept	0.033	0.00	9.111	0.00	-1.487	0.33
HAS	0.026	0.01	0.630	0.41	-0.116	0.87
HAF	0.026	0.27	-2.546	0.00	-2.284	0.00
Priceaggr					10.293	0.00
Panel B1: Confidence Interval for Indirect Effect						
	Mean	Std	Stderror	Lower	Upper	
HAS	0.7414	0.2687	0.0120	0.2853	1.2785	
HAF	-0.2620	0.2434	0.0109	-0.7433	0.1975	
Panel A2: Direct and Indirect Effects						
Dep. Variable	Actpass		Spread		Spread	
	Estimate	p-val	Estimate	p-val	Estimate	p-val
Intercept	0.010	0.00	9.111	0.00	2.761	0.21
HAS	0.008	0.00	0.630	0.41	0.032	0.97
HAF	0.008	0.00	-2.546	0.00	-2.889	0.00
Actpass					12.658	0.00
Panel B2: Confidence Interval for Indirect Effect						
	Mean	Std	Stderror	Lower	Upper	
HAS	0.6023	0.2339	0.0105	0.1876	1.1100	
HAF	0.3474	0.1483	0.0066	0.0987	0.6712	

Results on trading volume are shown in Table 4.11. The results indicate that the increase in volume is not driven by the aggressiveness in pricing behavior. However, trade aggressiveness is again positively related to overall market volume which is mechanical to a high portion since part of the volume would be represented by the number of aggressive human transactions. The results on market depth in Table 4.12 similarly show that price aggressiveness is unrelated to the quoting activity on the market.

Table 4.11: Direct and Indirect Effects on Volume

This table presents regression estimates on trading volume measured by number of transactions and price and trade aggressiveness according to Model 2 in Figure 4.5. Panel A1 / A2 depicts three regression on volume and price and trade aggressiveness respectively with the independent treatment variables HAS, HAF, and HR. Panel B1 / B2 further presents bootstrapping results and 95% confidence intervals of the indirect effects of treatments HAS and HAF.

Panel A1: Direct and Indirect Effects						
Dep. Variable	Priceaggr		Volume		Volume	
	Estimate	p-val	Estimate	p-val	Estimate	p-val
Intercept	0.033	0.00	16.960	0.00	16.905	0.00
HAS	0.026	0.01	0.424	0.00	0.421	0.00
HAF	0.026	0.27	0.600	0.00	0.602	0.00
Priceaggr					0.053	0.70
Panel B1: Confidence Interval for Indirect Effect						
	Mean	Std	Stderror	Lower	Upper	
HAS	0.0034	0.0098	0.0004	-0.0158	0.0230	
HAF	-0.0022	0.0060	0.0003	-0.0173	0.0066	
Panel A2: Direct and Indirect Effects						
Dep. Variable	Actpass		Volume		Volume	
	Estimate	p-val	Estimate	p-val	Estimate	p-val
Intercept	0.010	0.00	16.960	0.00	16.453	0.00
HAS	0.008	0.00	0.424	0.00	0.379	0.00
HAF	0.008	0.00	0.600	0.00	0.574	0.00
Actpass					1.008	0.02
Panel B2: Confidence Interval for Indirect Effect						
	Mean	Std	Stderror	Lower	Upper	
HAS	0.0445	0.0209	0.0009	0.0085	0.0917	
HAF	0.0259	0.0130	0.0006	0.0046	0.0560	

Table 4.12: Direct and Indirect Effects on Depth
This table presents regression estimates on market depth measured by the number of prevailing quotes and price and trade aggressiveness according to Model 2 in Figure 4.5. Panel A1 / A2 depicts three regression on depth and price and trade aggressiveness respectively with the independent treatment variables HAS, HAF, and HR. Panel B1 / B2 further presents bootstrapping results and 95% confidence intervals of the indirect effects of treatments HAS and HAF.

Panel A1: Direct and Indirect Effects						
Dep. Variable	Priceaggr		Depth		Depth	
	Estimate	p-val	Estimate	p-val	Estimate	p-val
Intercept	0.033	0.00	1.636	0.00	1.511	0.00
HAS	0.026	0.01	-0.114	0.02	-0.122	0.01
HAF	0.026	0.27	0.083	0.08	0.086	0.07
Priceaggr					0.121	0.10
Panel B1: Confidence Interval for Indirect Effect						
	Mean	Std	Stderror	Lower	Upper	
HAS	0.0082	0.0058	0.0003	-0.0017	0.0212	
HAF	-0.0041	0.0045	0.0002	-0.0155	0.0023	
Panel A2: Direct and Indirect Effects						
Dep. Variable	Actpass		Depth		Depth	
	Estimate	p-val	Estimate	p-val	Estimate	p-val
Intercept	0.010	0.00	1.636	0.00	1.517	0.00
HAS	0.008	0.00	-0.114	0.02	-0.124	0.01
HAF	0.008	0.00	0.083	0.08	0.077	0.11
Actpass					0.237	0.32
Panel B2: Confidence Interval for Indirect Effect						
	Mean	Std	Stderror	Lower	Upper	
HAS	0.0095	0.0100	0.0004	-0.0075	0.0312	
HAF	0.0056	0.0059	0.0003	-0.0045	0.0180	

In summary, the results on a market-period level show a consistently positive impact of an increasing number of agents on the market. The additional speed effect of fast agents leads to an additional improvement in efficiency, spreads, and market volume, but however to increases in profit dispersion. This confirms recent empirical results of HFT research on the positive effects of HFT, but it comes at the cost of higher profit dispersion, as shown in this experimental setting and quite apparent in the real world scenario.

More specifically, the increase in profit dispersion introduced by fast agents is around 5.7 %. In comparision, the improvement in efficiency amounts to around 17% and in spreads to 27 %. While these numbers need a pressing confirmation with real world data, it gives a first indication of the balance between improvement in market quality and discrimination of non-HFT with respect to speed. These findings generally add to the current HFT discussion on the fairness towards other groups of traders.

4.6 Summary

While HFT has become an important issue in financial markets, the impact of HFT on human trading behavior has not been studied yet. I fill this gap with the analyses on human traders. Computer agents induce more efficient trading behavior and higher price aggressiveness. In the context of the theory on competitive arousal, I can provide insight into the competitive reaction of human traders to trading agents. Due to a "de-emotionalization" effect by trading agents, human traders are less competitively aroused and thus exhibit more efficient trading behavior demonstrated by an increasing liquidity demand and higher price aggressiveness. However, the presence of fast agents induces a "time pressure" which increases arousal and aggressiveness and leads to higher efficiency.

Before making inferences on financial markets, there are several limitations of this study. I implement a comparably simple market structure as applied by Smith (1962) in order to rule out other effects that interact with agent and agent speed effects. In line with this structure, traders are assigned private values which rules out any informed trading behavior. As another consequence, I am only able to measure the allocative efficiency, but not the informational efficiency of the market. Apart from the ex ante known private values and costs, I have full transparency on the market. In reality, the transparency of the limit order book is not given for specific trading venues, such as dark pools.

This study contributes to the increasing amount of HFT literature and extend recent literature with respect to the experimental methodology and behavioral focus. Physiological measures give insight into differences in human trading behavior and emotional state which translates into significant differences in market efficiency and liquidity. Specifically, I contribute to neuro finance methodology by applying heart rates as a proxy for emotional arousal. I further contribute to research in experimental finance by the introduction of mixed computer- and human-based experiments. The application of these kind of experiments in asset markets is a very promising field for future research. In the context of the increase of AT and HFT in financial markets, mixed human-agent market settings also might serve as a better platform for certain research questions.

Furthermore, this study also has regulatory implications for AT and HFT. Despite the limitations of my design, the positive effects of computer agents is in line with previous empirical literature on market quality and market efficiency. The presence of trading agents improves overall efficiency and liquidity and also induces more efficient human trading behavior. However, although the trading speed of computer agents has a significant effect on the level of arousal and human quoting aggressiveness, it does not provide an additional positive market impact other than market depth. In the context of recent AT and HFT regulation, my results suggest that regulation to decrease AT volume harms market quality, but a decrease of HFT speed ceteris paribus should not have an overall effect on efficiency and liquidity.

Chapter 5

Conclusion and Outlook

The nature of financial markets and market participants have significantly changed within the last decades. In today's electronic markets, computerized trading agents are deployed for different purposes with different degrees of sophistication. Fuelled by discussions on their possible risks, there is a need for research on the effects of HFT on market quality and on human traders. The goal of this thesis is to gain more insight into the influence of HFT on market quality in general, and more specifically on price discovery and human trading behavior. This chapter summarizes the main contributions of this thesis, discusses its implications, and outlines avenues for future research in finance and information systems.

5.1 Contributions

The main contributions of this thesis are threefold: Firstly, Chapter 2 provides a background on the on-going evolution of financial markets, recent trends and the role of HFT in that context. Secondly, the empirical and experimental results in Chapter 3 and 4 give further insight into the information processing activities of HFT in price discovery and its impact on human trading behavior. Finally, I propose a framework for financial market quality and a market framework of human-computer interaction, as presented in Chapter 2 and 4 respectively. These frameworks provide a structured approach for the discussion of market quality and the analysis of trading behavior in mixed human-agent markets using physiological measurement.

Chapter 2 presents the basic foundations for the technological evolution of financial markets, measurement of market quality in financial markets, and discusses the role of HFT in this environment. It specifically addresses the following research question:

> **Research Question 1:** *How did market quality and external and internal factors of the trading landscape change over the last two decades?*

I focus the discussion on recent developments of technological nature in the context of market quality and a changing regulatory and competitive environment. In order to enable a structured analysis of market quality, I provide a conceptual framework to analyze market quality in three dimensions, namely market activity, liquidity, and information. It further incorporates external and internal effects which have important effects on financial market quality. A case study is presented in order to illustrate important changes in financial market quality and changes in the external and internal factors. Market quality dramatically improved over the last decades in most dimensions, such as spreads and volume. However, due to decreased tick sizes, market depth decreased and the increase in AT and HFT activity contributed to a decrease in trade sizes and an increase in message traffic. Due to the importance of HFT and AT in discussions on the structure of financial markets, it is thus important to understand the role of HFT in financial markets, as asked in the following research question:

> **Research Question 2:** *Which role does HFT play in modern financial markets and for market quality?*

The second part of Chapter 2 emphasizes the crucial role of HFT in the electronic evolution, which has been a driver for several improvements in terms of IT systems and innovations in business structures. It might be subject to higher regulatory scrutiny in the next years despite its positive effects on financial markets. I discuss the most important groups of HFT strategies. The different nature of these strategies demonstrates that it is difficult to make general statements on HFT without distinguishing between specific strategies. I further discuss approaches of HFT regulation and evaluate their possible effects on HFT activity and overall market quality and demonstrate the role of HFT based on empirical evidence in a case study. I show that

HFT play a crucial role for financial market quality. Despite the limitations of the dataset which identifies the activity of 26 HFT firms, the HFT volume is considerable. The results show that HFT is involved in has a stabilizing liquidity effect due to the fact that HFT consume liquidity when liquidity is cheap (i.e. spreads are narrow) and supply liquidity when it is expensive.

In Chapter 3, an empirical HFT study is presented which is based on transaction data provided by NASDAQ over 2 years, 2008-2009, for which HFTs and non-HFTs are identified. The analysis focuses on the role of HFTs and non-HFTs in processing hard index price information and soft news information. The research questions primarily concern the market impact of information events, information processing activities, and trading profits:

> **Research Question 3a:** *What is the market impact of hard and soft information events?*

> **Research Question 3b:** *How do HFT and NHFT process hard and soft information shocks?*

> **Research Question 3c:** *What is the value of speed in information processing?*

The results imply that HFTs and non-HFTs play complementing roles in processing hard and soft information. On one side, HFTs dominate non-HFTs in processing hard information by exhibiting a stronger reaction after the hard information shocks. Thereby, they create a stronger linkage between the futures and stock markets. Speed matters especially for hard information processing and realizing trading gains due to high short-run trading profits. On the other side, soft news information is primarily processed by non-HFTs and is incorporated into stock prices for a longer amount of time. These results contribute to the growing body of literature on financial innovation and HFT. While HFT research so far focuses more on the overall effect of HFT in financial markets, I specialize on information processing strategies and the role of speed.

Chapter 4 focuses on the influence of HFT on market quality and efficiency and on human trading behavior and emotions in a laboratory market. In order to systematically investigate these issues, a market framework for human-computer interaction is introduced which gives guidelines for studies involving human traders and computer agents in an experimental laboratory setting using NeuroIS tools. This framework is then applied in experimental study of a financial market scenario. In particular, a laboratory experiment is conducted based on the traditional design by Smith (1962) with human participants and computer agents with different trading speed. This experiment provides insight into the complex construct of "competitive arousal". In order to assess the emotional arousal of human participants, their heart rate is measured. In the analysis, I primarily focus on the effects on emotional arousal, human trading behavior, and direct and indirect effects on market quality, as formulated in the following research questions:

> **Research Question 4a:** *Are humans more or less emotionally aroused when trading against computer agents than against other humans?*

> **Research Question 4b:** *Do differences in emotional arousal affect trading behavior?*

> **Research Question 4c:** *Do differences in human trading behavior in turn translate into differences in market quality?*

Interestingly, human traders are less emotionally aroused in a market with slow agents than in a human-only market and more aroused in a fast agent scenario. In line with the theory of competitive arousal, rivalry is mitigated when agents are present since competitiveness between humans decreases. However, counteracting "time pressure" effects that are a result of fast agent activity increase the emotional arousal of participants. Consequently, human traders price their orders less aggressively when interacting with slow agents. However, the time pressure induced by fast agents has a direct effect on aggressiveness and leads to more aggressive pricing of order as compared to the treatment with human only interaction.

The positive effects of computer agents are in line with previous empirical literature on market quality and market efficiency. Especially the presence of fast trading agents induces more efficient human trading behavior in terms of aggressiveness which translates into higher efficiency and liquidity. However, it also increases profit dispersion among traders which points towards a discrimination of slower traders.

5.2 Implications

This thesis addresses several regulatory concerns of HFT in financial markets and provides more insight for discussions regarding regulatory and policy changes. Additionally, trading venues are equally interested in these topics in order to understand the role of HFT for their business models, to overcome market frictions, and prevent market failure by regularly adapting their market structure to the dynamic environment.

While some regulatory measures might have negative effects on market quality, specific rules such as circuit breakers and fees on message traffic or order-to-trade ratios might be beneficial to curb some of the unwanted effects of HFT activity. Circuit breakers for example address one concern of regulators which is the strong interlinkage between different markets. This could cause erroneous information to travel faster between markets and thus create or worsen market disruptions. Findings in Chapter 2 strengthen regulatory discussions on market-wide circuit breaker rules, i.e. trading halts that are triggered by abnormally high volatility within a certain time period. These rules have been revised for example by the SEC (cf. SEC, 2012c, "Market-Wide Circuit Breaker Approval Order").

Recent developments have shown a trend towards machine-processable news and a general hardening of soft information. In addition to existing concerns associated with HFT, these algorithms might give rise to even greater concerns than traditional HFT algorithms due to misinterpretation of and overreaction to events. In my analyses, I cannot confirm this development although the analysis is limited to a data sample from 2008 to 2009. In terms of soft information processing, I can refute concerns that HFTs overreact to soft information events. HFTs seem to rather withdraw from the market than actively trade on soft information events which might ease some of these concerns towards soft information processing at least for the analyzed time period.

My findings further point to an edge of HFTs over non-HFTs in the speed of hard information processing. Thus, concerns could be raised whether HFT might lead to overreactions in the short run, but in the long run, they rather mitigate volatility due to the inversion of their trading behavior. Furthermore, the results also strengthen previous literature on HFT contribution to short-term price discovery (cf. Brogaard et al., 2013).

Furthermore, the presence of different types of agents has several implications for human traders, such as individual investors. While I generally show lower aggressiveness towards computer agents and higher time pressure in the presence of faster agents, investors should take behavioral considerations into account next to the technological changes in financial markets in order to adapt their trading strategies.

5.3 Future Research

Although HFT is currently under some regulatory scrutiny, technological innovation plays an important role for market participants and market operators in order to adapt to the changing competitive environment. The processing power and sophistication of algorithms used by buy-side investors improves with the growing technological possibilities and adapt to the different types of markets structures and types of traders. Due to this fact, the diversity of HFT strategies must be taken into account when conducting research in this field. Furthermore, the technological innovation also changes the market conditions and interaction with human traders. The technological evolution in market places also leads to a general speeding up of markets and an increasing interaction with computerized trading agents. While these effects were central in the experimental study in Chapter 4, there is still need for research on these kind of mixed human-agent markets and how these markets affect human trading behavior and emotional arousal.

Diversity of HFT strategies

As suggested by Hagströmer and Nordén (2012), different HFT strategies might have different effects on market quality. Thus, future research should take the distinction between different strategies into account, such as market making and arbitrage strategies. Furthermore, HFT might also have different effects on different markets. As discussed in Section 2.1.2, HFT has overly positive effects on equity and futures markets and is a group of traders that these types of markets aim to attract. However, foreign exchange markets claim that overall volume in FX trading decreased because HFT activity driving away other groups of traders (Reuters, 2013a). Thus, it is important to understand the different roles of HFTs in these markets and the different strategies that they apply.

Next to the discussion on market quality, regulatory discussions also involve the risk involved with the growing importance of HFT. The Flash Crash on May 6th, 2010 was a striking demonstration of systemic risks that are incorporated in financial markets. Opponents claim stricter regulation of HFT as a group regarding their market making activities from which trading venues profit, but on which they also rely heavily. Although a majority of U.S. retail advisor believed in an "overreliance on computer systems and high-frequency systems" that caused the Flash Crash (c.f. Kirilenko et al., 2011), academic literature have not found any negative effects of HFT and moreover supports evidence on positive effects. As for the growing literature on HFT that researches into the volatility and risk effects of HFT, more research has to be done to shed light on the behavior of HFT in different market situations, e.g. periods of high market volatility and market crashes. Furthermore, it still needs to be understood whether HFT exacerbate these kind of extreme market situations.

Large-scale Experiments of Dynamic Market Environments

The application of mixed computer- and human-based experiments in asset markets is a very promising field for future research in experimental finance and NeuroIS. Especially in the context of the increase of AT and HFT in financial markets, mixed human-agent market settings might serve as a better platform for certain research questions. The proposed market framework for human-computer interaction further provides possibilities for further extensions in financial and information systems research.

Firstly, the experimental design can be more complex than the one presented. 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 on this market microstructure issue has already been conducted by Bloomfield et al. (2011). Thus, experimental environments are an ideal setting to analyze effects of variations in market design and complement empirical research on historical data. Furthermore, differences in interface design could also lead to differences in behavior and help to improve financial decision making. An example is demonstrated by Astor et al. (2013) who present a game for learning to control emotions and fulfilling numerical tasks in parallel and thereby demonstrate the effectiveness of a tool for emotion regulation. Furthermore, the type of agent not restricted to competitive computer agents, but can also be applied to the group of supportive computer agents that e.g. rather provide liquidity than compete for trading profits. Using computer agents as market makers would be an interesting aspect to improve market design, specifically with respect to differences in performance and effects on liquidity of a human market maker and a computerized market maker.

Secondly, the analysis of "competitive arousal" still offers a wide range of research possibilities due to the many dimensions involved, especially in the interface with other areas in IS, such as social networks, behavioral and NeuroIS, and human-computer interaction. Specific examples include e.g. the research on "technostress" and information overflow. This kind of stress may be caused by extensive human-computer interaction (cf. Riedl et al., 2012) and can be discussed both from the perspective of NeuroIS and the design of user interfaces. In this context, more sophisticated technology can help to gain deeper insight into different dimensions of these effects, such as eye-tracking technology, and neurological tools, such as fMRI, in order to evaluate alternative interface designs with respect to their psychophysiological response.

Finally, the market framework for human-computer interaction 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. However, transfers to industries other than the financial market setting applied in the experimental study are also possible. One example includes recent work on agent-mediation in automated negotiations, often applied in e-commerce, as described by Guttmann et al. (1998) and He et al. (2003). Gimpel et al. (2013) further present a guideline in the form of a "NeuroIS framework for emotion regulation in management" which combines NeuroIS tools in a managerial decision environment in order to enable more sophisticated decision making of managerial executives.

5.4 Summary

In this chapter, I presented the main contributions of this thesis which consists of an overview of the electronic evolution of financial markets, empirical and experimental evidence of HFT activity in financial markets, and methodological guidelines for research on market quality and on the interaction of humans and computer agents in a dynamic market environment.

I further outlined several fields for possible future research. There is need for further research on HFT especially during extreme market events as well as on the difference between HFT strategies in different markets. Furthermore, the methodological approach of the market framework for human-computer interaction offers a wide range of applications and extensions for future finance and information systems research. In the context of ever-evolving financial markets, it is crucial to understand the role of innovation, but also to assess the influence of regulatory and market design changes on the different dimensions of market quality.

Appendix A

Sample Stocks and Robustness Checks (Chapter 3)

A.1 List of Sample Stocks

Table A.1 presents the 40 sample stocks and the absolute and relative HFT activity. *Total* denotes the average total number of trades per stock day, *HFTrades* the number of trades involving an HFT. $Abs.Hinit$ and $Abs.Hpass$ denote the absolute number of HFT initiated and passive trades respectively, while $Rel.Hinit$ and $Rel.Hpass$ is the relative percentage.

Table A.1: Sample Descriptives

Ticker	*Total*	*HFTrades*	*Abs.Hinit*	*Abs.Hpass*	*Rel.Hinit*	*Rel.Hpass*
AA	25,114	20,808	11,074	15,548	0.44	0.62
AAPL	80,133	61,555	39,180	40,798	0.49	0.51
ADBE	20,428	14,565	8,640	9,035	0.42	0.44
AGN	4,204	2,288	1,640	979	0.39	0.23
AMAT	31,595	25,738	13,403	19,403	0.42	0.61
AMGN	23,413	14,956	8,276	9,440	0.35	0.40
AMZN	26,606	17,824	13,752	7,596	0.52	0.29
AXP	26,900	21,427	12,996	14,430	0.48	0.54
BHI	11,960	9,498	7,204	5,128	0.60	0.43
BIIB	10,651	6,087	4,469	2,561	0.42	0.24
BRCM	29,737	22,892	13,414	15,375	0.45	0.52
CB	6,797	4,846	3,713	2,301	0.55	0.34
CELG	14,440	8,289	5,761	3,893	0.40	0.27
CMCSA	36,859	30,790	16,649	23,115	0.45	0.63
COST	18,202	12,700	9,160	6,513	0.50	0.36
CSCO	58,631	48,597	26,048	36,284	0.44	0.62
CTSH	14,013	9,580	5,843	5,632	0.42	0.40
DELL	35,368	28,372	14,447	20,965	0.41	0.59
DIS	19,013	15,837	8,728	11,420	0.46	0.60
DOW	17,254	13,848	7,912	9,565	0.46	0.55
EBAY	28,002	21,564	11,016	15,429	0.39	0.55
ESRX	9,212	4,942	3,803	1,780	0.41	0.19
GE	58,184	51,038	27,354	40,142	0.47	0.69
GENZ	10,773	6,065	4,502	2,434	0.42	0.23
GILD	23,151	14,571	8,615	8,658	0.37	0.37
GLW	18,094	14,852	7,701	10,776	0.43	0.60
GOOG	20,548	15,430	11,512	7,682	0.56	0.37
GPS	15,935	13,403	8,018	9,599	0.50	0.60
HON	11,197	8,559	5,448	5,293	0.49	0.47
HPQ	27,743	22,083	11,155	16,225	0.40	0.58
INTC	61,676	51,344	26,530	39,351	0.43	0.64
ISRG	4,863	3,233	2,483	1,320	0.51	0.27
KMB	4,234	2,693	1,844	1,382	0.44	0.33
KR	12,735	10,183	6,014	7,149	0.47	0.56
MMM	9,141	6,646	4,662	3,625	0.51	0.40
MOS	12,561	9,670	6,962	5,203	0.55	0.41
PFE	33,071	28,208	12,984	22,729	0.39	0.69
PG	23,249	17,711	9,082	13,100	0.39	0.56
PNC	10,806	8,007	6,159	3,871	0.57	0.36
SWN	10,111	7,500	5,748	3,577	0.57	0.35
All Stocks	22,915	17,705	10,348	11,983	0.46	0.46

A.2 Reverse Ordering of HFT and NHFT net trading in VARX Model

Table A.2: Impact of Information Shocks on Net Trading - Reverse Ordering
This table presents aggregated coefficients of HFT and non-HFT net trading after an information shock under the assumption that non-HFT trade before HFT. The VARX model is implemented with the respective trading variables as the dependent variables. The independent variables are lagged and contemporaneous HFT and non-HFT order flow and returns. All variables are aggregated into ten second intervals and standardized using mean and standard deviation for each stock and each trading day. Panel A reports aggregated impact on initiating and passive net trading for HFT (HFT_{init}, HFT_{pass}) and non-HFT ($NHFT_{init}$, $NHFT_{pass}$) as well as their respective difference ($Diff$). Panel B reports result for VIX shocks and Panel C for news events. SR denotes the contemporaneous impact in the short run, LR denotes the aggregated impact for the following 12 ten second intervals, i.e. 2 minutes after the information shock, $LR - SR$ denotes the long-run impact minus the short-run impact. Variables are aggregated per stock-day and tested using double clustered standard errors on stock and trading day. T-statistics are in parentheses. ***, **, and * denotes significance at the 1%, 5%, and 10% level respectively.

	Panel A: Impact of Futures Shocks on Net Trading					
	Initiating Order Flow			*Passive Order Flow*		
	HFT_{init}	$NHFT_{init}$	$Diff$	HFT_{pass}	$NHFT_{pass}$	$Diff$
SR	0.240***	0.179***	0.061**	-0.102***	-0.272***	0.170***
(t-stat)	(9.06)	(13.40)	(2.51)	(-6.75)	(-12.93)	(10.89)
LR	-0.009	0.350***	-0.359***	-0.263***	-0.189***	-0.073
(t-stat)	(-0.22)	(5.26)	(-5.04)	(-7.51)	(-3.29)	(-1.37)
LR-SR	-0.249***	0.171***	-0.420***	-0.160***	0.083	-0.243***
(t-stat)	(-6.71)	(2.69)	(-5.57)	(-5.37)	(1.64)	(-4.77)

Table A.2: Impact of Information Shocks on Net Trading - Reverse Ordering - continued

	Panel B: Impact of VIX Shocks on Net Trading					
	Initiating Order Flow			*Passive Order Flow*		
	HFT_{init}	$NHFT_{init}$	$Diff$	HFT_{pass}	$NHFT_{pass}$	$Diff$
SR	0.029***	-0.021***	0.049***	0.017***	-0.010**	0.028***
(t-stat)	(4.88)	(-5.77)	(9.75)	(4.51)	(-2.06)	(6.36)
LR	0.079***	-0.164***	0.243***	0.218***	-0.020	0.238***
(t-stat)	(3.93)	(-7.39)	(7.92)	(11.78)	(-0.97)	(10.24)
LR-SR	0.051***	-0.143***	0.194***	0.201***	-0.009	0.210***
(t-stat)	(2.68)	(-7.09)	(6.71)	(11.83)	(-0.51)	(9.92)

	Panel C: Impact of News Shocks on Net Trading					
	Initiating Order Flow			*Passive Order Flow*		
	HFT_{init}	$NHFT_{init}$	$Diff$	HFT_{pass}	$NHFT_{pass}$	$Diff$
SR	0.025	0.076**	-0.051	-0.067**	-0.049*	-0.018
(t-stat)	(0.96)	(2.35)	(-1.46)	(-1.99)	(-1.86)	(-0.62)
LR	0.088	0.377**	-0.289*	-0.394***	-0.304*	-0.090
(t-stat)	(1.01)	(2.23)	(-1.95)	(-3.92)	(-1.87)	(-0.58)
LR-SR	0.064	0.301**	-0.237*	-0.327***	-0.256*	-0.071
(t-stat)	(0.76)	(2.00)	(-1.74)	(-4.02)	(-1.66)	(-0.48)

A.3 Trading Profits - Robustness over Time

Table A.3: HFT Profits after Information Shocks - Robustness over time

This table presents HFT revenue after information events. Panel A shows profits after futures shocks, Panel B after VIX shocks, and Panel C after news shocks. We distinguish between the pre-crisis period (Jan-Aug 2008; Panel A1, B1, C1), the crisis period (Sep 2008-June 2009; Panel A2, B2, C2), and the post-crisis period (July 2009-Dec 2009; Panel A3, B3, C3). *Real* denotes the total realized trading revenue of initiating and passive HFT. *Fast*, *Slow*, and *VSlow* are fictitious revenues under the assumption that HFT: (1) start at occurrence of an information shock with 0 inventory, (2) only make trades 0 seconds (*Fast*), 10 seconds (*Slow*), and 20 seconds (*VSlow*) after the information event, and (3) sell their inventory 60 seconds or 120 seconds after the information shock. All profit variables are in $, aggregated per stock-day, and tested using double clustered standard errors on stock and trading day. T-statistics are in parentheses. ***, **, and * denotes significance at the 1%, 5%, and 10% level respectively.

	Panel A1: Futures Shock - 2008 Pre-Crisis								
	Initiating Volume				*Passive Volume*				*All*
	Real	*Fast*	*Slow*	*VSlow*	*Real*	*Fast*	*Slow*	*VSlow*	
0 sec	98.32***	98.32***			-4.98	-4.98			93.35***
(t-stat)	(4.26)	(4.26)			(-0.43)	(-0.43)			(3.19)
10 sec	185.04***	117.36***	67.22***		-40.75*	-25.98*	-14.08		144.29***
(t-stat)	(3.74)	(3.74)	(3.62)		(-1.74)	(-1.91)	(-1.36)		(2.62)
20 sec	196.06***	103.01***	34.43	58.67***	-66.27**	-18.87	-20.92	-26.58**	129.79**
(t-stat)	(3.12)	(3.62)	(0.68)	(3.89)	(-2.20)	(-1.36)	(-1.51)	(-2.59)	(2.24)
60 sec	284.38***	25.18	57.76**	48.40***	-190.16***	-11.91	-36.23***	-38.26***	94.22
(t-stat)	(2.74)	(0.61)	(2.01)	(3.25)	(-3.50)	(-0.78)	(-4.31)	(-3.22)	(1.00)
120 sec	495.12***	39.00**	27.95	51.84***	-227.22**	9.30	-20.26*	-22.68***	267.91
(t-stat)	(3.18)	(2.05)	(0.60)	(2.78)	(-2.51)	(0.53)	(-1.90)	(-3.27)	(1.61)

Table A.3: Impact of Futures Shocks on Trading Revenues - continued

Panel A2: Futures Shock - 2008 Crisis									
0 sec	1202.70***	1202.70***			-396.65***	-396.65***			806.05***
(*t*-stat)	(5.35)	(5.35)			(-3.42)	(-3.42)			(4.14)
10 sec	1297.97***	743.40***	550.54***		-579.40***	-317.25***	-257.44***		718.58***
(*t*-stat)	(6.02)	(6.01)	(5.76)		(-3.85)	(-4.13)	(-3.43)		(4.28)
20 sec	1280.11***	574.60***	287.65***	418.02***	-655.02***	-242.22***	-199.98***	-213.09***	625.09***
(*t*-stat)	(6.47)	(6.35)	(6.10)	(5.92)	(-3.76)	(-4.04)	(-3.50)	(-3.46)	(4.25)
60 sec	1245.34***	313.31***	129.57***	135.32***	-822.50***	-136.04***	-103.75***	-110.94***	422.83***
(*t*-stat)	(6.63)	(6.23)	(4.42)	(5.13)	(-4.00)	(-3.98)	(-3.22)	(-3.41)	(3.86)
120 sec	1089.03***	154.05***	91.15***	53.41**	-888.73***	-78.13***	-69.27***	-43.45*	200.30
(*t*-stat)	(4.72)	(3.71)	(3.55)	(2.09)	(-4.03)	(-3.16)	(-3.25)	(-1.88)	(1.47)
Panel A3: Futures Shock - 2009 Post-Crisis									
0 sec	65.96***	65.96***			-22.71***	-22.71***			43.25***
(*t*-stat)	(5.12)	(5.12)			(-3.92)	(-3.92)			(4.70)
10 sec	98.13***	70.33***	27.63***		-34.30***	-24.90***	-9.21***		63.83***
(*t*-stat)	(4.53)	(4.67)	(3.61)		(-4.51)	(-4.04)	(-4.05)		(3.25)
20 sec	106.56***	64.76***	23.27***	18.57***	-49.31***	-26.76***	-12.97***	-9.61***	57.25***
(*t*-stat)	(5.49)	(4.91)	(3.95)	(5.97)	(-4.41)	(-3.75)	(-4.13)	(-4.02)	(4.96)
60 sec	145.16***	54.83***	9.78**	19.27***	-67.53***	-16.85**	-8.23***	-8.60**	77.62***
(*t*-stat)	(4.93)	(3.88)	(1.98)	(2.74)	(-3.78)	(-2.25)	(-3.19)	(-2.43)	(3.63)
120 sec	218.80***	51.34***	10.12	18.63**	-98.19***	-15.47**	-10.45***	-7.16	120.61***
(*t*-stat)	(5.19)	(3.70)	(0.91)	(2.20)	(-4.67)	(-2.12)	(-3.01)	(-1.33)	(3.50)

Table A.3: Impact of VIX on Trading Revenues - continued

	Panel B1: VIX Shock - 2008 Pre-Crisis								
	Initiating Volume				*Passive Volume*				*All*
	Real	*Fast*	*Slow*	*VSlow*	*Real*	*Fast*	*Slow*	*VSlow*	
0 sec	237.35***	237.35***			-99.35***	-99.35***			137.99***
(*t*-stat)	(5.45)	(5.45)			(-4.02)	(-4.02)			(3.28)
10 sec	473.40***	280.78***	191.22***		-218.21***	-143.11***	-73.06**		255.19***
(*t*-stat)	(5.29)	(4.90)	(4.89)		(-4.11)	(-4.29)	(-2.46)		(3.24)
20 sec	593.37***	206.41***	208.14***	178.81***	-298.38***	-98.93***	-115.18***	-84.27***	294.99***
(*t*-stat)	(5.02)	(5.02)	(4.68)	(5.10)	(-3.84)	(-3.95)	(-3.64)	(-3.69)	(2.96)
60 sec	1039.93***	156.43***	139.07***	149.07***	-558.12***	-77.72***	-86.53***	-90.46***	481.81**
(*t*-stat)	(4.89)	(4.38)	(3.93)	(4.46)	(-4.37)	(-3.80)	(-4.09)	(-4.11)	(2.40)
120 sec	1212.25***	87.71***	81.43***	102.05***	-756.17***	-41.00***	-47.88***	-69.65***	456.08**
(*t*-stat)	(5.24)	(2.87)	(2.69)	(3.79)	(-4.39)	(-3.13)	(-3.39)	(-3.51)	(2.13)
	Panel B2: VIX Shock - 2008 Crisis								
0 sec	391.58***	391.58***			-147.11***	-147.11***			244.48***
(*t*-stat)	(5.26)	(5.26)			(-2.90)	(-2.90)			(3.46)
10 sec	685.23***	352.39***	330.61***		-294.90***	-155.38***	-136.78***		390.33***
(*t*-stat)	(5.40)	(5.54)	(5.19)		(-3.24)	(-3.39)	(-2.93)		(3.38)
20 sec	878.56***	244.74***	333.67***	300.15***	-427.81***	-120.20***	-171.89***	-135.76***	450.74***
(*t*-stat)	(5.26)	(5.28)	(4.69)	(5.26)	(-3.55)	(-2.79)	(-3.97)	(-3.45)	(3.18)
60 sec	954.47***	113.02***	113.29***	109.20***	-661.78***	-70.92***	-92.10***	-92.35***	292.68***
(*t*-stat)	(5.90)	(4.27)	(5.08)	(4.17)	(-4.23)	(-3.42)	(-3.66)	(-4.08)	(2.96)
120 sec	1079.48***	90.40***	80.58***	67.48***	-767.66***	-31.79***	-57.29***	-58.81***	311.82***
(*t*-stat)	(5.95)	(3.22)	(3.65)	(3.80)	(-4.07)	(-2.59)	(-3.06)	(-4.04)	(3.68)

Table A.3: Impact of VIX on Trading Revenues - continued

	Panel B3: VIX Shock - 2009 Post-Crisis								
0 sec	92.70***	92.70***			-40.27**	-40.27**			52.44***
(*t*-stat)	(4.25)	(4.25)			(-2.25)	(-2.25)			(4.87)
10 sec	169.89***	94.27***	74.97***		-67.97	-48.94***	-18.30		101.92***
(*t*-stat)	(4.11)	(5.40)	(2.88)		(-1.59)	(-3.53)	(-0.59)		(4.39)
20 sec	182.76***	97.68***	52.41	32.68	-160.97***	-30.45*	-75.60***	-54.94***	21.78
(*t*-stat)	(3.22)	(3.58)	(1.10)	(0.67)	(-3.69)	(-1.68)	(-2.80)	(-3.77)	(0.77)
60 sec	172.37	85.24***	-5.78	-2.26	-211.01***	-10.46	-26.22***	-27.59**	-38.64
(*t*-stat)	(0.98)	(7.45)	(-0.13)	(-0.06)	(-3.83)	(-0.64)	(-3.04)	(-2.32)	(-0.27)
120 sec	444.69***	34.33**	28.69***	12.15	-324.43***	-10.08	-19.31**	-11.90	120.26*
(*t*-stat)	(4.07)	(2.38)	(2.77)	(0.39)	(-4.54)	(-1.04)	(-2.01)	(-0.94)	(1.74)

Table A.3: Impact of News on Trading Revenues - continued

	Initiating Volume				*Passive Volume*				*All*
	Real	*Fast*	*Slow*	*VSlow*	*Real*	*Fast*	*Slow*	*VSlow*	
Panel C1: News Shock - 2008 Pre-Crisis									
0 sec	19.29**	19.29**			-9.40***	-9.40***			9.89
(*t*-stat)	(2.44)	(2.44)			(-3.23)	(-3.23)			(1.15)
10 sec	112.32**	85.35**	26.90***		-32.13***	-25.50***	-6.53		80.20*
(*t*-stat)	(2.37)	(2.20)	(2.65)		(-2.68)	(-3.09)	(-1.21)		(1.84)
20 sec	21.38	41.22**	-38.12	18.28*	-10.08	-22.38*	13.60	-1.28	11.29
(*t*-stat)	(0.45)	(2.02)	(-0.75)	(1.78)	(-0.45)	(-1.84)	(1.27)	(-0.16)	(0.28)
60 sec	-1.38	30.24	-91.31	42.77*	78.31	3.50	65.21*	15.69	76.93
(*t*-stat)	(-0.02)	(1.55)	(-1.37)	(1.88)	(1.21)	(0.24)	(1.73)	(0.92)	(0.82)
120 sec	77.56	53.07*	-31.25	-0.81	10.49	2.21	34.23	14.59	88.05
(*t*-stat)	(0.82)	(1.87)	(-0.54)	(-0.05)	(0.13)	(0.13)	(1.02)	(0.69)	(1.04)
Panel C2: News Shock - 2008 Crisis									
0 sec	8.78**	8.78**			-23.64**	-23.64**			-14.86
(*t*-stat)	(1.97)	(1.97)			(-2.18)	(-2.18)			(-1.58)
10 sec	22.70	25.44*	-2.86		-20.26*	-25.84**	5.73		2.44
(*t*-stat)	(1.27)	(1.93)	(-0.29)		(-1.88)	(-2.25)	(0.46)		(0.29)
20 sec	109.23**	41.45**	17.63*	50.15	-15.10	-34.55***	11.40	8.04	94.13*
(*t*-stat)	(2.15)	(2.15)	(1.86)	(1.43)	(-0.40)	(-2.90)	(0.44)	(0.49)	(1.67)
60 sec	80.23	15.27*	34.92	-34.53	-21.10	21.16	-11.83	21.34	59.13
(*t*-stat)	(1.33)	(1.92)	(1.19)	(-1.07)	(-0.51)	(0.58)	(-0.51)	(1.17)	(1.06)
120 sec	197.78	22.48	55.57	-0.36	-55.59	12.57	5.80	26.72	142.19*
(*t*-stat)	(1.57)	(1.20)	(1.31)	(-0.02)	(-0.66)	(0.82)	(0.26)	(1.01)	(1.85)

Table A.3: Impact of News on Trading Revenues - continued

	Panel C3: News Shock - 2009 Post-Crisis								
0 sec	4.43**	4.43**			-6.79**	-6.79**			-2.36
(*t*-stat)	(2.10)	(2.10)			(-2.44)	(-2.44)			(-1.63)
10 sec	-82.41	-104.13	21.66		134.63	151.39	-16.67**		52.22
(*t*-stat)	(-0.69)	(-0.89)	(1.44)		(0.79)	(0.89)	(-2.23)		(0.98)
20 sec	-70.82	-104.80	32.59	1.39	130.32	154.59	-19.37*	-4.92*	59.50
(*t*-stat)	(-0.58)	(-0.89)	(1.36)	(0.49)	(0.77)	(0.91)	(-1.94)	(-1.91)	(1.11)
60 sec	70.82***	13.51	24.51	-24.41	-101.91***	-32.27**	-9.55	1.38	-31.09
(*t*-stat)	(3.42)	(1.64)	(1.30)	(-1.36)	(-3.64)	(-1.99)	(-1.21)	(0.19)	(-1.00)
120 sec	95.82*	9.51	32.10	9.09	-194.00***	-27.19	-24.99	-17.31**	-98.18*
(*t*-stat)	(1.94)	(0.75)	(0.70)	(0.48)	(-3.84)	(-1.57)	(-1.64)	(-1.97)	(-1.73)

Appendix B

Experimental Design and Instructions (Chapter 4)

B.1 Participant Instructions

Instructions

[We include English translations of the instructions. Please note that the instructions are only translations for information; they are not intended to be used in the lab. The instructions in the original language were carefully polished in grammar, style, comprehensibility, and avoidance of strategic guidance.]

This is an experiment in market decision-making. During the entire experiment, your heart rate, skin conductance, and pulse will be recorded for further analysis. You can earn real money during this experiment. What you earn depends on your decisions. These instructions explain how you can win a certain amount of money, based on your decisions, which will be paid out to you at the end of the experiment. If you follow the instructions carefully and make good decisions, you can earn a considerable amount of CASH. The profit numbers in the experiment are in monetary units (MU) (→①). **1 MU** corresponds to a payout of **1 Eurocent**, i.e. you get 1, – € for 100 MU.

You trade a fictitious asset during **4 market scenarios** (→② right). Each stage consists of **6 periods** (→② left), lasting **2.5 minutes** each. Before starting the real experiment, first a set of 4 trial periods is being played. Profits gained during these trial periods are not relevant for your payout at the end of the experiment. You will participate in 24 periods that are relevant for your payout. The structure of the market scenarios and periods are explained below.

During each period, each participant is allowed to trade **up to 6 units** (→①) of the fictitious asset. Exactly **one unit** is traded per transaction. The participants of each period consist of **you and [11 other participants in this room / 5 participants in this room and 6 computer-based agents]** (→③). The 12 market participants are composed of 6 sellers and 6 buyers. You will be assigned the role of rather a <u>**buyer**</u> or a <u>**seller**</u>. You find this information on your information sheet and it will furthermore be displayed in ③. You keep your randomly assigned role during the **whole** experiment.

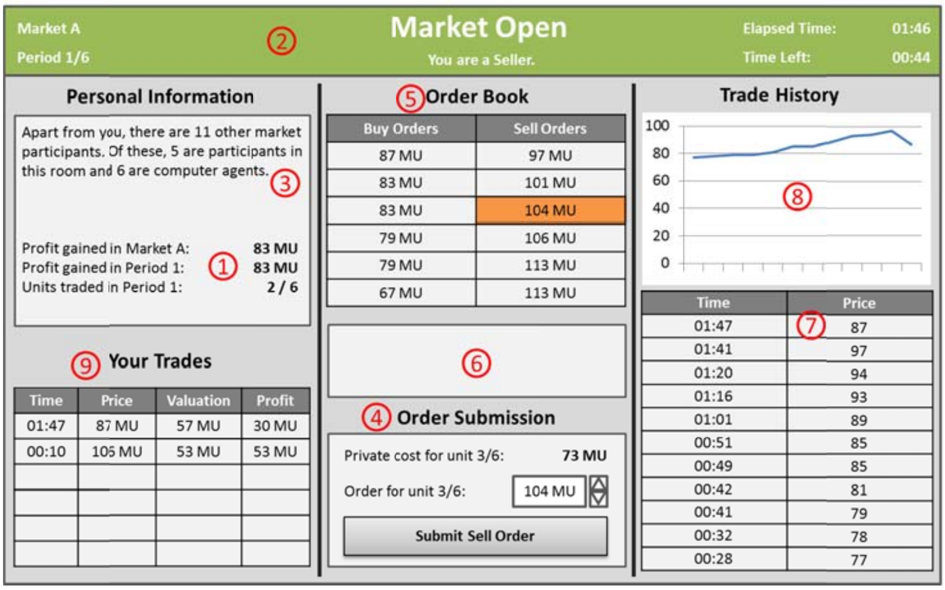


Figure 1: Trading Interface

Your Payoff

<u>As a Buyer</u>

During the transaction periods of the experiment, the **private value** of the current unit is displayed in (→④). This valuation indicates the fictitious asset's value for the particular buyer. The value is drawn from an interval 0 to 200 MU and **decreases** within a period for each unit traded. A buyer can bid for the fictitious asset during each period (→④). A bid represents the price a buyer is willing to pay for the fictitious asset. In a transaction, only the highest bid is taken into account. In order to achieve the **highest bid**, your bid price has to **exceed the currently highest bid price** in the market (→⑤). You cannot withdraw your offer, but update it by entering a new bid price. In case of a transaction, you realize a **profit** (→①) of the difference of your private valuation and the transaction price.

Profit = private value – transaction price

Example 1: Your private value is 60 MU and you buy at a price of 45 MU, therefore you realize a profit of 15 MU: 60 MU - 45 MU = 15 MU.

Example 2: Your private value is 130 MU and you buy at a price of 140 MU, therefore you realize a loss of 10 MU: 130 MU - 140 MU = -10 MU.

<u>As a Seller</u>

During the transaction periods of the experiment, the **private cost** of the current unit is displayed in (→④). These costs indicate the fictitious asset's value for the particular seller. The costs are drawn from an interval 0 to 200 MU and **increase** within a period for each unit traded. A seller can make offers for the fictitious asset during each period (→④). An offer represents the price a seller is willing to pay for the fictitious asset. In a transaction, only the lowest offer is taken into account. In order to achieve the **lowest offer**, your offer price has to be lower than the **currently lowest offer price** in the market (→⑤). You cannot withdraw an offer, but update it by entering a new offer price. In case of a transaction, you realize a **profit** (→①) of the difference of the transaction price and your private costs.

Profit = transaction price – private cost

Example 1: Your private costs are 75 MU and you sell at a price of 90 MU, therefore you realize a profit of 15 MU: 90 MU - 75 MU = 15 MU.

Example 2: Your private costs are 70 GE and you sell at a price of 50 MU, therefore you realize a loss of 20 MU: 50 MU - 70 MU = -20 MU.

<u>General</u>

A **trade is executed,** if

a) a buyer submits a **bid higher than or equal** to **the currently lowest offer**
b) a seller submits an **offer** being **lower than or equal** to the **currently lowest bid**.

In case of a trade, the trade price is executed at the order price already placed in the market, <u>**not**</u> at the newly made order. If the newly entered **bid** is higher than the currently lowest **offer**, the trade is executed for the existing **bid**. If the newly entered offer is below the currently highest bid, the trade is executed for the existing **bid**.

In case of two bids being made at the same price, the earlier entered bid is executed. If you do not trade during a period, you realize a profit of 0 MU.

Example:

You are a seller. There is an offer for 40 MU.

- *…You enter an offer for 50 MU → No trade takes place*
- *… You enter an offer for 40 MU → A trade is executed. You gain 40 MU for the unit sold.*
- *You enter an offer for 30 MU → A trade is executed. You gain 40 MU for your unit sold.*

Trading Interface (see Figure 1)

1.) Participant's Information

Your **private value / costs** of the current unit will be displayed to you in the middle of your trading interface below **"Order Submission"** (→④). As soon as you traded a unit, you will receive your private value / costs for the next unit and are able to trade it. Furthermore, you will see your role, the number of the current market stage as well as the number of the current period in the **status bar** (→②), in the upper part of the screen. The **infobox** (→①) at the left side of the screen contains information about your current gains and already traded units.

2.) Submitting bids and offers

As long as you have not made 6 trades yet, you can submit **exactly one bid, respectively one offer** at a time. You can do this by entering the integer value using the Numpad (see Figure 2) or by pressing the **+/- buttons** to increase or decrease the limit price. You can submit the order by pressing the **Enter** key. A confirmation is displayed in the middle of the screen (→⑥) and your order is being recorded in the **order book** (→⑤). The order book collects all current bids and sorts them by price. On the left side of the order book you find the bids in descending order, and on the right side of the order book you find the offers in ascending order. The highest bid and the lowest offer are displayed in bold at the top of the list. Your own bid is highlighted in orange.

Figure 2: Numpad

3.) Trade execution

Once you make a successful bid, the transaction is executed and you get a visual **confirmation** in (→⑥), as well as an audio confirmation via your headphones. Furthermore the transaction price is displayed in the trading history and the price chart (→⑧), which is visible to all market participants, as well as in your trade history (→⑨). The profits realized up to now will be updated in the infobox (→①) and you will get to see your information on the next tradable unit in (→④).

4.) Transition between periods

A timeout of the current period will be displayed to you in the middle of the status bar (→②). After a short break between two periods, the market will be reopened. You will receive an audio signal via your headphones as soon as the market starts. Afterwards you start trading the first unit. The exact time until the reopening will be displayed on the right side of the status bar (→②).

Payment

Gains and losses gained in every market stage are summed up and displayed in the infobox (→①). Please note: At the end of the experiment, **exactly two of the four market stages are being paid out**. After the experiment you roll the dices to specify the profits of the market stages that are being paid out. Furthermore you will receive an amount of 10, - € for participating in the experiment. Losses during the market stages are being offset with gains from the stages. The payout for each market stage cannot be below 0 €. Your total payout is at least 10, - €.

In case of further questions regarding the experiment, please give the experimenter a hand signal. Please wait until the experimenter is at your place, and ask your question as quietly as possible.

B.2 Emotion Regulation Questionnaire

erq01	When I want to feel more positive emotion, I change what I am thinking about.
erq02	I keep my emotions to myself.
erq03	If I want to feel less negative emotion, I change what I am thinking about.
erq04	If I am feeling positive emotions, I am careful not to express them.
erq05	When I am faced with a stressful situation, I make myself think about it in a way that helps me stay calm.
erq06	I control my emotions by not expressing them.
erq07	When I want to feel more positive emotion, I change the way I am thinking about the situation.
erq08	I control my emotions by changing the way I think about the situation I am in.
erq09	When I am feeling negative emotions, I make sure not to express them.
erq10	When I want to feel less negative emotion, I change the way I'm thinking about the situation.

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