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The Economics of Algorithmic Trading

Zur Erlangung des akademischen Grades eines

Doktors der Wirtschaftswissenschaften

(Dr. rer. pol.)

von der Fakultät für

Wirtschaftswissenschaften

der Universität Karlsruhe (TH)

genehmigte

Dissertation

von

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Tag der mündlichen Prüfung: 04.08.2009

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2009 Karlsruhe

Acknowledgements

I would like to express my gratitude and thanks to my advisor Prof. Dr. Christof Weinhardt for his support, trust, and advice throughout the preparation of this dissertation. He always knew the right time to encourage me and the right time to challenge me. Without his support my research would not be what it is today.

I would also like to thank Prof. Dr. Marliese Uhrig-Homburg for her support as my co-advisor. She was always capable of providing a different point of view on my results. My thanks also go to Prof. Dr. Gerhard Satzger who acted as my examiner and Prof. Dr. Martin Ruckes, the chairman of my committee.

I would be remiss if I forgot to mention my colleagues at the Institute of Information Systems and Management (IISM) and the Information and Market Engineering (IME) graduate school. I would like to thank my colleague Matthias Burghardt who had to endure my complaints about empirical research. I would also like to thank Benjamin Blau for interesting and interdisciplinary discussions. My thanks also go to all of my co-authors, but especially Terrence Hendershott for his insight and positive impact on my approach to research.

Finally, but most importantly, I would like to thank my family. I thank my Father not only for his help editing but also for teaching me to be a conscientious and engaged teacher and researcher. I thank my Mother who taught me to be humble throughout this process and life in general. Primarily I thank my wife Fee and my children Kiana and Juliana. Fee's support and understanding was unwavering, I dedicate this work to her. I also thank my children who had to suffer throughout this process but were also my inspiration to finish. I hope that you all feel that it was worth it.

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Chapter 1

Introduction

Financial markets have undergone a dramatic technological transformation over the past 10 years. Electronic and centralized limit order books dominate the organized securities exchange landscape. Automated execution in alternative trading systems, dark-pools, and electronic communication networks are available to investors to trade in most securities. Traditional market-maker markets, like the New York Stock Exchange, have resorted to allowing participants to interact directly with other investors using an electronic limit order book, thereby circumventing humans in the trading process. Traditional banks and fund companies as well as other financial institutions have invested in trading technology to improve their trade generation and monitoring processes. The automation of this process is typically called *Algorithmic Trading* and the users of this technology are called *Algorithmic Traders*. The abbreviation *AT* is used interchangeably for both throughout.

AT is commonly defined as the use of computer algorithms to manage the trading process (Hendershott, Jones, and Menkveld (2008)). This includes generating, submitting, deleting, and modifying orders in any number of securities. The process also includes determining the best market in which to trade, called smart order routing in Foucault and Menkveld (2008), and is becoming increasingly important as the market fragmentation process accelerates. Investors are using AT technologies to source liquidity in multiple markets and reduce the cost thereof. The use of AT in this type of situation is rather straightforward. Computers continuously monitor multiple markets for liquidity and submit orders that minimize transaction costs. Investors are also using AT to process and trade on information gathered from a wide array of sources both traditional (for instance market data) and novel (such as machine readable news and interactive data)[1].

The following chapters illustrate the study of AT as demanders and suppliers of liquidity, as well as the information content of AT trade. In light of the recent press coverage of AT, the paucity of academic studies of AT, and the explosion in their use, the study of their trading behavior is timely and important.

1.1 Motivation

As roughly 43% of equity trading (by volume) in Germany is executed by AT, and since more than 33% [2] is executed by AT in US securities markets, it is reasonable to argue that a study of their behavior is warranted. AT is used to trade in multiple securities simultaneously, in equity (Hendershott, Jones, and Menkveld (2008)), foreign exchange (Chaboud et al. (2009)), and derivatives markets. Between the 2006 and 2008, exchanges worldwide began upgrading their trading systems to meet the increased strain due to rising AT volumes. The London Stock Exchange[3], NYSE - Euronext, Deutsche Boerse (DB), and the Toronto Stock Exchange[4] all released low-latency versions of their electronic trading systems to meet these demands. AT may increase system strain, in that they trade more often, but also because when they trade they may use smaller trade sizes and a greater number of orders per executed share (Hendershott, Jones, and Menkveld (2008)). In their 2007 annual report, the DB highlighted the importance of AT in their recent growth and the continued importance of AT for future growth, as well as the system strain of increased

[1] See: the Interactive Data (XBRL) initiative at www.sec.gov

[2] Source: 2008 speech by Andrew Donohue to the SIFMA Institutional Brokerage Conference - http://www.sec.gov/news/speech/2008/spch060408ajd.htm

[3] See: www.londonstockexchange.com - Tradelect

[4] See: www.tsx.com/quantum

AT activity. Unfortunately, despite the importance and pervasiveness of AT, we lack insight into their trading behavior.

Despite this increasing importance and influence of AT, little is known about their impact on securities markets. Interestingly, while little is known about AT, they generate a lot of bad press. AT are typically made responsible for market crashes, increased volatility, and instability in securities markets. The March 2^{nd} edition of the German financial newspaper *Handelsblatt* cited Karl Fickel, a traditional mutual fund manger, as follows[5]:

> "I am convinced that trading programs in phases like in the past few weeks increase (market) fluctuations.[6]"

The implicit economic criticism is that AT programs cause transitory volatility. Transitory volatility is unrelated to the fundamental value of a firm and market conditions and is considered to be have negative effects on securities markets. Comments like the one above are quite common in the popular press. However as far back as September 15th, 2005 the Economist recognized the potentially positive impact of AT. They wrote:

> "Simple software-based traders have been around for many years, but they are now becoming far more sophisticated, and make trades worth tens of billions of dollars, euros and pounds every day. They are proving so successful that in the equity markets, where they are used to buy and sell shares, they already appear to be outperforming their human counterparts, and it now seems likely that their success will be repeated in foreign-exchange markets too. Proponents of robo-traders claim that, as well as making more money, they can also help to make markets more stable. And, of course, being made of software, they do not demand

[5]This is a direct translation of the original text - from German to English.

[6]Source: Handelsblatt 02.03.2009 - Computer im Boersenhandel auf dem Vormarsch

lunch breaks, holidays or bonuses[7]."

The article highlights the potential for *robo-traders* to make markets more stable, in addition to appearing to be more profitable. Remarkably, these conflicting opinions co-exist in the press and have yet to be tested in the academic literature. This dissertation begins to fill the gap between what we know and what we think about AT.

1.2 What is Algorithmic Trading?

Algorithmic trading is an excellent example of the far-reaching effects of technology in financial markets. Computer algorithms are now replacing humans in the trading process. The main difference between AT and human trading is the direct interface of algorithms with the market, without human intervention. Algorithms are processing market (and other) data at extremely high frequencies and automatically generating trades to profit from this data. Algorithms may also help to reduce the fixed and variable costs of trading by reducing search and monitoring costs (Biais and Weill (2008)), which may be driving recent increases in stock markets volume (Chordia, Roll, and Subrahmanyam (2007)).

There are a number of uses for AT, but one of the primary goals is to reduce transaction costs (seek liquidity). Transaction costs can be reduced by monitoring multiple markets for liquidity and trading where posted prices are best. Algorithms may also be used to reduce the market impact of large orders, by splitting them into smaller slices and optimally executing each slice (Almgren and Chriss (2000)). Algorithms are relatively good at these computational tasks. In contrast to their non-algorithmic (*human*) counterparts, AT are able to continuously monitor multiple markets and securities. Humans are at a distinct disadvantage to computer algorithms and are increasingly being replaced in the search for liquidity.

[7]Source: Page 1 Sept. 15th, 2005 the Economist Print Edition Technology Quarterly - The march of the robo-traders.

As securities exchanges increase their levels of automation (Jain (2005)), humans are being placed at an even greater disadvantage. As exchanges speed up, humans are left to observe market data with a delay when compared to algorithms. The formula below formalizes the concept with a simple example:

$$AT_{inf} = (P_t, P_{t-1})$$

$$Hum_{inf} = (P_{t-1})$$

Where AT_{inf} represents the AT information set and Hum_{inf} the human information set, P is a price, and t indexes time. In the example above, humans see prices only *after* AT have had a chance to process *and act* on the information. Essentially AT see the most recent price and humans see prices with a lag and must infer the next price, knowing that AT have already observed that price. The impact this can have in practice is addressed in Chapter 4. Essentially, at the moment a human has observed a price, it is outdated. The effect this can have is seen in Chapter 5 where AT and human trades are studied. This does not mean that humans are being entirely replaced by algorithms, only that their efforts are perhaps shifting to more value-added tasks such as fundamental analysis and portfolio allocation.

Algorithmic technologies are also being used to process market data for reasons other than liquidity seeking. This processed data may also be used to supply and demand liquidity profitably. For instance, algorithms can monitor spot and derivatives markets for deviations in price from fundamental values, and trade on this information. Due to their ability to simultaneously, and almost costlessly, monitor and manage executions in multiple markets, they are better able to reliably profit from these deviations. Imagine a scenario where throughout the day deviations exist in the prices of DAX stocks and DAX futures due to random liquidity shocks. Algorithms continuously monitoring these markets are better able, due to their speed advantage, to identify situations where prices have deviated. Also, due to their ability to manage the trading process, they may be better able to reduce the risks associated with trading on these deviations. This could in turn have the positive effect of making prices more efficient, a hypothesis tested in Chapter 5.

To develop a firm grasp of what AT is, it is also important to know what AT is *not*! Although quite similar in their description, algorithmic trading is not the same as program trading[8]. Program trading is the simultaneous purchase or sale of at least 15 securities totalling at least $1,000,000 USD in a coordinated and systematic fashion. Program trading may be executed via an algorithm but it isn't a requirement of the NYSE-program. In 2007, the NYSE proposed a change to the program trading definition[9]. The NYSE rule change proposal was in fact never implemented, due to industry resistance. The proposal would have modified the definition of two of eight program trading categories to cover proprietary and agency algorithmic program trading. This would have essentially segregated NYSE program trades into algorithmic and non-algorithmic. The NYSE proposal mirrors the above division of AT into liquidity seeking and proprietary trading, which are also the commonly accepted industry interpretations of the application of AT.

1.3 Technological Aspects of Algorithmic Trading

Rapid advances in information technology and communications networks have transformed the business of trading and the demands on exchanges. Algorithmic trading is arguably only one of the most recent steps in a long technological march. Algorithmic trading, is dependent on the automation of trade execution and routing, as well as on a number of other innovations. The most important innovation that set the stage for AT is the centralized limit order market - a market that is particularly well suited to automation (Stoll (2006)). Jain (2005) highlights the increasing trend

[8]See: `www.nyse.com` - Program Trading description
[9]See: NYSE Information Memo 07-52 on Program Trading under rule 80A.

towards automation in stock exchanges and the positive effects thereof. He finds that the introduction of electronic trading reduces the cost of capital and increases the liquidity of traded shares. Technology in this context has been shown to increase liquidity, likely, due to an improvement in the information environment. Technology is increasing the amount of information available about the demand and supply of a stock, and this increased information is being transformed, at a minimum, into higher liquidity.

1.3.1 Development of Algorithmic Trading

Figure 1.1 highlights the development of AT and the trading environment starting from the 1970's and ending in the present. During this time, trading has evolved from a purely manual process to one involving an increasingly complex interplay of people, process, and technology[10]. A number of trends have driven electronic trading and AT. The most prominent trend is the general shift towards automation in all industries through the introduction of commodity computer systems. An important second factor was the introduction of the Internet and inexpensive communication technologies. These technologies allowed markets, intermediaries, and investors to inexpensively connect to one another. Brokers began the automation process in the 1980's by providing sales traders with computer terminals to transmit and monitor orders submitted to the floor of stock exchanges. The broker changes were followed shortly thereafter by exchanges (Easley, Hendershott, and Ramadorai (2007)) that began to automate order matching and offer floor traders enhanced order management technologies; even then, orders were mostly handled manually. In the 1990's and into the new millennium, brokers and exchanges began offering more complex market access tools. A number of access technologies and protocol innovations, such as Smart Order Routing Systems (SORT), and the Financial Information eXchange-Protocol (FIX - see 1.3.2), made trading and investing more technically complex,

[10]The first electronic stock exchange was the Toronto Stock Exchange in 1976 that introduced the Computer Aided Trading System - CATS

and also accessible. Investors have also automated the trade monitoring process in-house by using order management systems (OMS) and other AT technologies.

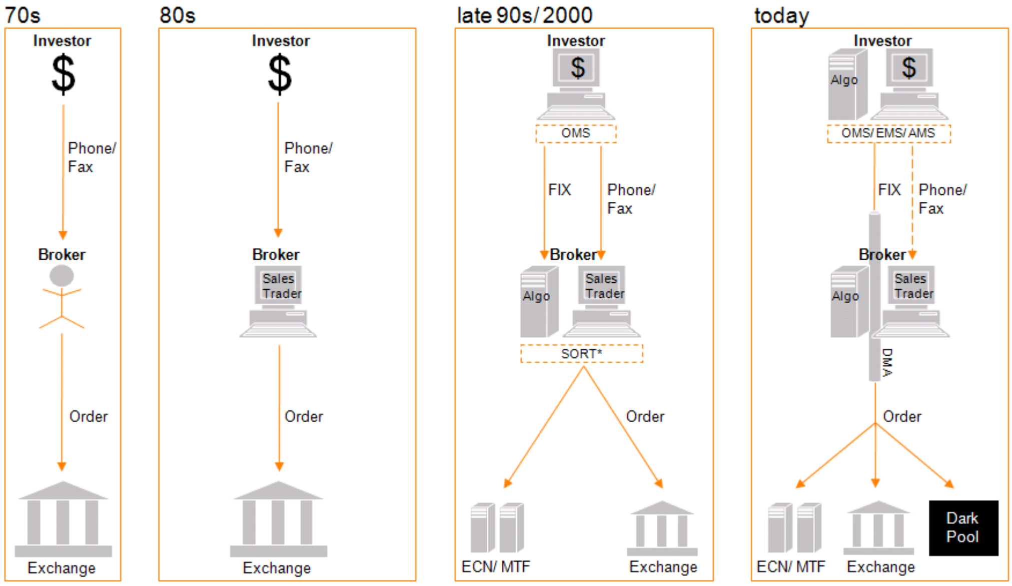

Figure 1.1: Development of Algorithmic Trading: The figure illustrates the technological development of AT throughout the 1970s to today.

The number of execution venues[11] and technologies involved[12] in securities trading have made today's AT reality what was unimaginable only a short time ago. The sheer number of algorithms available to investors today is so high that banks have begun to employ Algorithmic Management Systems to monitor and manage the algorithms that monitor and manage the trade process. Two other recent developments - presented below - have changed, in distinct ways, how AT access markets and the benefits to trading algorithmically.

1.3.2 FIX Trading Protocol

The FIX protocol was developed in the 1990's by a consortium of banks, exchanges and regulators. FIX was designed to speed up and standardize the message traffic between investors and exchanges. Standardization is achieved in that FIX interfaces are offered by all major exchanges which allows investors to develop a single trading

[11] Electronic communications networks, exchanges, internal and dark pools
[12] OMS, event management systems, algorithm management systems

application with the ability to connect to a number of markets. Given the amount of time and money invested in developing AT systems, this reduction in development costs presents a significant improvement in the trading environment.

Technically the FIX protocol sits in the application layer with other common communications protocols such as HTML and FTP. See Figure 1.2 for a better understanding of the networking aspects of the FIX protocol. By being embedded directly in the communication protocol, FIX is both fast and without much of the technical overhead that would encumber a stand-alone protocol.

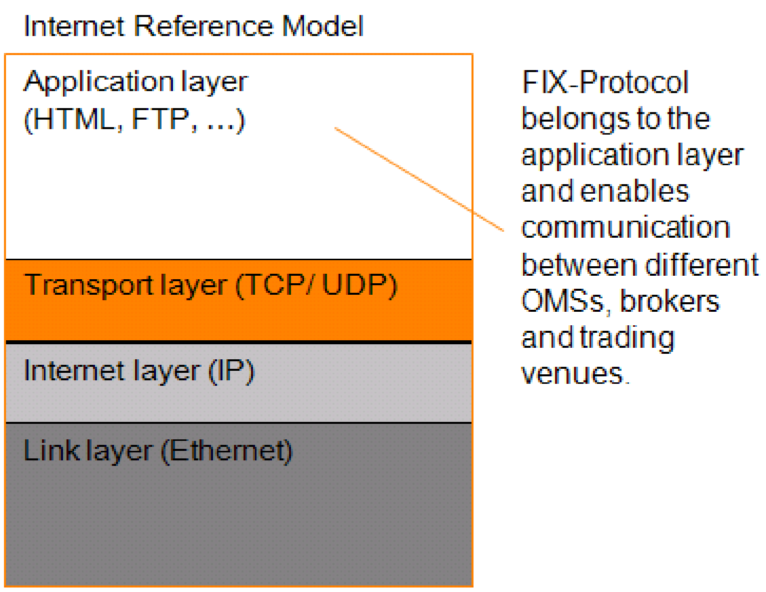

Figure 1.2: FIX Trading Protocol: The figure shows the placement of FIX within the Internet reference model.

Besides speed, FIX offers the benefit of standardization. Before the introduction of the FIX protocol, financial institutions either had to agree on a specific language definition or manually process trading instructions. Both scenarios are dramatically more expensive than today's fully electronic and standardized trading environment.

To illustrate the content of a FIX trade see Figure 1.2 showing a sample message between two banks.

The message contains a quote for a call option that expires in January 2010. The bid (5.00) and ask (5.25) prices and size (10) as well as the strike price are coded

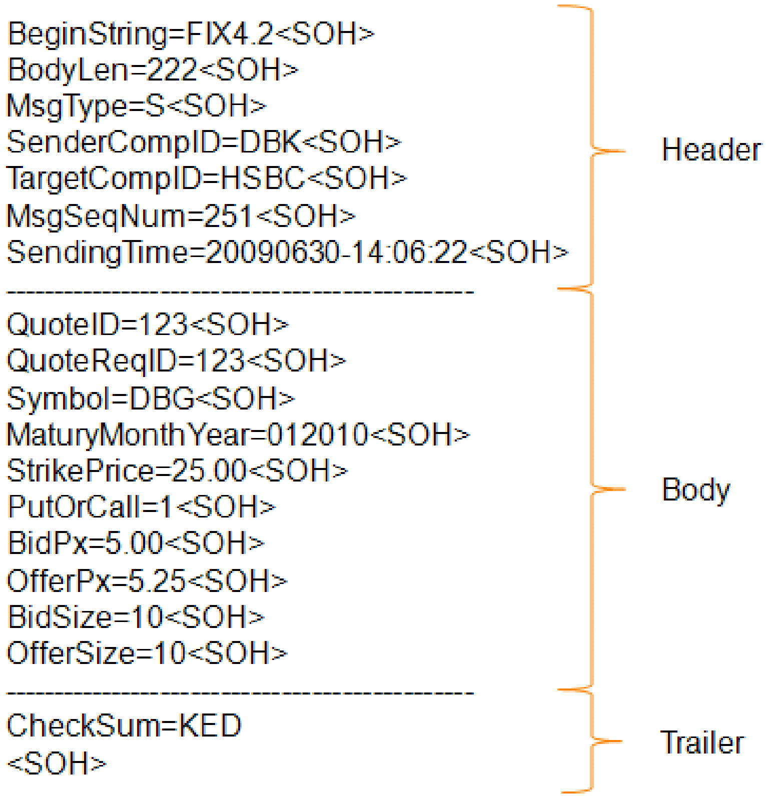

Figure 1.3: FIX Trading Message: This figures illustrates a sample FIX message between two banks.

directly into the message body. The message header contains information about the source and destination of the quote and the exact message sending time. A response message, not included for reasons of brevity, would include similar information and whether or not the receiving bank accepted the terms of trade offered in the message.

1.3.3 Co-location, Connectivity, and Data Dissemination

One of the most important factors in high-frequency trading is receiving and acting upon information before other participants can or do. This is achieved by placing the trading application in close proximity to the market. Exchanges and other IT service providers have a number of offerings that effectively bring the market *closer* to trading applications. The DB, and other major exchanges worldwide, offer co-location services to financial institutions. Essentially the institutions rent space in server rooms that are owned and operated by the exchanges. By co-locating in the exchange server rooms, participants are able to reduce the physical distance between trading applications, in most cases algorithms, and the market, and thereby reduce latency. Often even these co-location services lack the space needed to meet the demand of financial institutions. This undersupply attests to the value of latency. Other IT-service providers have similar offerings that are not physically co-located but close enough to the market infrastructure to render the difference negligible. Figure 1.4 shows the infrastructure at the DB with and without co-location.

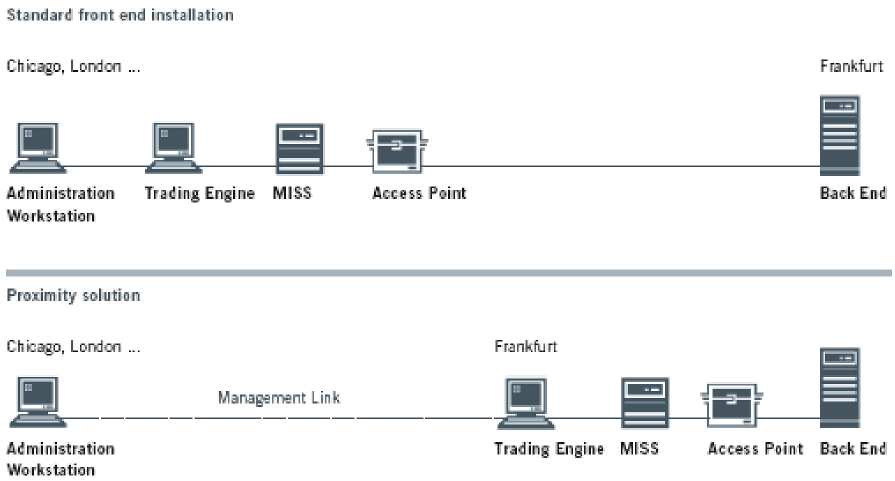

Figure 1.4: Co-location services: The figure illustrates the placement of IT-systems, with and without co-location, required to access the market. Source: `www.deutscheboerse.de` - proximity services pg. 12

The most important difference is the location of the trading engine as this is where algorithms reside. With the proximity solution, shown in Figure 1.4 the entire trading infrastructure in located within the DB IT-environment. Besides reducing access time to the market, co-location ensures similar up-time and infrastructure availability as for the Xetra trading system.

Another important factor is connectivity, i.e. the network being used to contact the market. Exchanges generally offer a number of ways to connect to their markets. To access Xetra, participants can use a normal Internet connection or leased lines provided by the DB or connectivity providers (cf. Deutsche Telekom or BT

Systems). Leased lines are available in a number of connection speeds depending on the participant's requirements and willingness to pay. Connection speeds range from 64 kilobits per second to one gigabit per second. One can only assume that faster connections are worth the added cost.

Exchanges have also made numerous changes to their data dissemination services, which distribute trade and order book data to subscribers. Because of the investment in trading technologies and the increased usage of AT, exchanges are increasingly distributing trade and order book updates in real-time, rather than delayed. Another important change is the manner in which data is being disseminated. In the past, exchanges disseminated order book snap-shot, or netted, data every couple of seconds. This level of granularity is no longer enough to meet the demands of AT and other high-frequency traders. The increase in the granularity and timeliness of available data has surely driven some of the recent increases in AT and this trend is expected to continue.

1.4 Research Questions

The goal of this dissertation is to study how AT contributes to the price discovery process, as well as to study how AT contributes to the liquidity production and consumption process. The research contained herein lays the foundation for a deeper analysis of a number of interesting questions on AT. The research questions are broken down into two distinct topics: information and liquidity. The first research question is as follows:

RQ1: Are AT more informed than humans?

This question is addressed in two sections but with the same general econometric techniques. This question is of great importance to regulators, market operators, and investors alike. If AT, and therefore roughly 50% of trades in Germany, are uninformed, then they are more likely to cause market instability and contribute to transitory volatility. The second research question deals with liquidity consumption and productions and is as follows:

RQ2: Does AT contribute to or diminish market liquidity?

If AT continuously monitor the market for liquidity, what effect does this have on market liquidity as a whole? The question is critical in that we have few indications from the literature as to how AT demand and supply liquidity. We are essentially unable to venture an educated guess as to when and why AT supply and demand liquidity and whether or not they exacerbate or smooth it. These two questions are addressed in the following chapters.

1.5 Overview and Structure

In Chapter 2, a general literature overview is introduced on the subject of AT and liquidity and price discovery as well as the intersection of the two. Chapter 3 presents some general institutional details. Chapter 4 is an event study of the effect of a latency reducing system upgrade on liquidity and information. The chapter is based on joint working paper between the author of this dissertation and a fellow Ph. D. student at the University of Karlsruhe, Andreas Storkenmaier. In Chapter 5 the results of an in-depth analysis of AT is presented. The chapter is based on a joint work with the author of this dissertation and Terrence Hendershott at the University of California at Berkeley, Haas School of Business. Chapter 6 concludes and presents future work.

Chapter 2

Literature Review

This chapter provides an overview of the literature. A more focused review of the literature is provided again in Chapters 4 and 5 as it applies to the specific sections. The literature presented in this chapter represents the general context, rather than the specific relevance of each paper. This chapter also presents the literature regarding the interdependence of liquidity, information and price discovery. Most importantly, the current literature gaps are highlighted, specifically with respect to AT.

2.1 Algorithmic Trading

Only recently have financial researchers begun to provide indirect evidence on the positive effects of AT on financial markets. More specifically, financial researchers have only now begun to focus their attention on these specific traders. Two recent working papers Hendershott, Jones, and Menkveld (2008) and Chaboud et al. (2009) are the first to address the topic. Hendershott, Jones, and Menkveld (2008) use a proxy for AT, message traffic, and find that increases in AT improve liquidity and the efficiency of prices at the NYSE. Chaboud et al. (2009) use a more direct instrument to study AT in foreign exchange markets. They identify AT as orders that are submitted using the electronic brokering systems (EBS) offered by Reuters, while orders submitted via other systems are classified as human. Chaboud et al. (2009) study find that AT order-flow is less informed and that AT orders do not contribute to volatility. Both results are interesting given the representation of AT as pariahs in the media.

Both working papers define AT similarly. Hendershott, Jones, and Menkveld (2008) define AT as:

> "...the use of computer algorithms to automatically make certain trading decisions, submit orders, and manage those orders after submission.[1]"

The focus of the Hendershott, Jones, and Menkveld (2008) definition is on the automation of the entire trading process. Where Hendershott, Jones, and Menkveld (2008) focus on the individual activities Chaboud et al. (2009) describe AT in the foreign exchange market as a process

> "...where computer algorithms directly manage the trading process at high frequency.[2]"

The focus of the Chaboud et al. (2009) paper is not only on the trading process, but also the speed with which the process is managed, i.e. high frequency. Competing definitions do exist but are similar to the above two and do not further contribute to our understanding of the topic. The essence is that computers are managing, with the help of algorithms, all or parts of the trading process. The definitions above leave some room for interpretation. AT is perhaps best described as a continuum of automation decisions in trading and investing.

Algorithmic technologies are also being used to automate the process of gathering, processing and interpreting information (Tetlock (2007), Tetlock, Saar-Tsechansky,

[1]Source: Page 1 of Hendershott, Jones, and Menkveld (2008).
[2]Source: Page 1 of Chaboud et al. (2009).

and Macskassy (2008)). Tetlock (2007) reports on a trading strategy based on a simple news reading algorithm that can beat the market. While the trading strategy would be implementable without AT, the trading signals generated by the algorithm would not. Tetlock, Saar-Tsechansky, and Macskassy (2008) study an intra-day version of the strategy presented in Tetlock (2007) and attain similar results with respect to profitability. These articles show that the boundary between what an algorithm can analyze and what a human can analyze is not stationary. An article in the Financial Times[3] entitled *'City trusts computers to keep up with the news'* explains the recent trend of using computer algorithms to gather and process news reports. Clearly the use and application of computer algorithms in the investment and investment management process is in its early stages.

Market participants use different algorithms to solve different trading problems. Algorithms are used to reduce the market impact of trade by spreading them over time, as in Barclay and Warner (1993a). They are being used to consolidate fragmented order flow using smart order routing technologies (Foucault and Menkveld (2008)). Statistical and index arbitrage strategies typically employ computer algorithms to monitor multiple markets simultaneously (Gatev, Goetzmann, and Rouwenhorst (2006)) and manage orders in the multiple markets. The primary focus in these strategies is to process large amounts of market data and information to maximize trading and investing goals.

In a recent working paper, Hasbrouck and Saar (2009) break AT into two separate categories. They refer to these categories as Proprietary Trading and Statistical Arbitrage (PT/SA), and Algorithmic Agency (AA) trading. PT/SA trading is trade associated with proprietary trading desks within a bank or hedge funds and boutique trading shops to profit from short-term information. Algorithmic agency trading is trading on behalf of customers using AT mainly to minimize implicit transaction costs. The PT/SA traders are using AT to process information faster and to profit

[3]Source: `http://www.ft.com/cms/s/0/bb570626-ebb6-11db-b290-000b5df10621.html`

from this, and are therefore more sensitive to the latency of exchange systems. This is similar to the theoretical traders in Goettler, Parlour, and Rajan (2009), that have no intrinsic motivation to trade and simply seek to profit from their informational advantages. Agency algorithmic traders are characterized by the repetitive nature of their trade. They achieve their trading goals by slicing an entire trade into smaller pieces to reduce the price impact, as in Almgren and Chriss (2000).

2.2 Liquidity

Liquidity is defined as the ability to exchange an asset for money at a price as close as possible to the equilibrium price (O'Hara (1995)). The more a transaction price deviates from it's equilibrium price, the less liquid is the market. An equilibrium price is defined as the price that clears a market given fully informed participants Grossman and Stiglitz (1976). This relationship is also important for price discovery, the greater the liquidity risk, the lower the incentive and ability of an informed investor to correct a price deviation; this follows directly from the results of Amihud and Mendelson (1986).

One generally measures liquidity in stock markets as the difference between the buying and selling price of an asset. More specifically, while the quoted spread (Copeland and Galai (1983)) $(Ask - Bid)/(Ask + Bid)$ is most often used as a good approximation of liquidity costs, it measures only hypothetical trading costs. The analyses in the following chapters often make use of more exact calculations and variables which measure other dimensions of liquidity such as effective spreads, volume, and depth (Chordia, Roll, and Subrahmanyam (2000)).

Other studies also focus on observed individual liquidity measures rather than expected market-wide liquidity. In Hendershott and Moulton (2007) and Venkataraman (2001) the focus is on bid-ask spreads, and therefore individual liquidity measures. Theoretically, a number of early market microstructure studies of liquidity also focused on spreads (Copeland and Galai (1983, Glosten and Milgrom (1985, Kyle (1985)). Specifically these studies laid the foundation for the study of informed trading in securities markets from the perspective of liquidity suppliers. The results showed that positive spreads exist to compensate liquidity suppliers for the risks of trading with more informed traders.

Liquidity is not only of interest to market microstructure researchers. (Amihud and Mendelson (1986)) argue that lower trading costs, measured as the bid-ask spread, translate into higher securities prices. This finding has recently become increasingly clear and relevant. The credit crisis demonstrated that the more illiquid an asset, the lower its expected value; unfortunately this realization came too late for most market participants.

The unit of analysis in this dissertation is at the individual trade level rather than daily or weekly levels as in Pastor and Stambaugh (2003), who study liquidity as a cross-sectionally priced risk factor and find support that liquidity is, in fact, priced. The implications are that liquidity and the costs thereof are an important part of asset pricing, i.e. the higher the liquidity costs, the lower is the asset price, and are therefore first order determinants of asset prices and deserving of in-depth study.

2.3 Price Discovery

One of the central predictions of theoretical market microstructure is that order flow affects prices. This prediction follows from both inventory-based models (Amihud and Mendelson (1980) and Stoll (1978)) and information-based models (Easley and Ohara (1987),Glosten and Milgrom (1985), and Kyle (1985)) of market making. The information models assume that some investors have information (are informed) about future price changes and that others do not (are uninformed). The trades of informed investors lead to permanent price adjustments to the information they convey. In market microstructure, we usually measure information ex-post. A common ex-post measurement is a permanent price change in a stock price (Hasbrouck (2002)). Other competing measures are the weighted price contribution presented in Barclay and Warner (1993b), the variance ratio as used in Amihud and Mendelson (1987) and the R^2 of regressions of returns on individual trades and time intervals.

O'Hara (1995) highlights the intuition that trades reveal the underlying information of the trader and thereby affect the behavior of prices. For instance in the Glosten and Milgrom (1985) model, traders with bad-news will submit sell orders until the security price fully reflects their information. Traders with good news will submit buy orders until the price reflects their information. Although the results are originally obtained in a market-maker setting, they hold for limit order markets as well (Parlour and Seppi (2008)).

Hasbrouck (1995) and Hasbrouck (1991a) are built on the intuition that measuring prices *ex-post* for permanent changes proxies for information. This laid the foundation for the empirical work in the area of market microstructure and information that followed, including this dissertation. The econometric tools presented in Hasbrouck (1991a), Hasbrouck (1991b), and Hasbrouck (1995) are based on vector auto-regressions, and are used to detect permanent changes in the random-walk component of securities prices. Hasbrouck (1995) associated this permanent price change with the information a trader possesses. By measuring the permanent changes and attributing them to a specific trader group, one can identify informed traders, inasmuch as informed is measured as a continuum rather than a discreet value.

The price discovery process takes place when the order flow of different subsets of the trading population is aggregated into a market. The better the aggregation process, the better are the prices attained. Frictions such as transaction costs and taxes as well as other factors such as psychological biases ensure that prices are *noisy proxies* for asset values. The process of price discovery has been studied in a number of microstructure settings (Barclay and Hendershott (2003) , Hasbrouck (2002), Hasbrouck (1995), Hasbrouck (1991a) , Hasbrouck (1991b), Hendershott, Jones, and Menkveld (2008), and Huang (2002)). Hasbrouck's work, as mentioned above, provides the theoretical-empirical framework for most of the following analyses[4].

Price discovery is essentially the process of incorporating new information into securities prices, thereby keeping them efficient. It represents the trading process by which informed investors translate information into profit. Taking the simplest case in which a trader receives private information that a company's share price is too low, an informed investor will purchase shares until the price reflects the informed investor's information. This example abstracts away from a number of important factors; most importantly it ignores transaction costs (liquidity) and risk. An informed investor will in fact take the contemporaneous and the future transaction costs into account when exploiting this information. This highlights the importance of liquidity in the price discovery process.

One of the problems with testing market microstructure theories is that theoretically there exist informed and uninformed investors, but the predictions are unclear as to who these are. Data limitations are usually such that inference is required to determine whether or not an investor is informed. For instance in Boehmer and Wu (2008) the researchers use a data set derived from the NYSE audit trail. The audit trail data categorizes trades into four groups: individuals; institutions; non-NYSE market-makers; and specialists. They further differentiate the order-flow into regular institutional trades, index-arbitrage program trades, and other program trades. The main finding in Boehmer and Wu (2008) is that the order flow of each group affects prices differently. They also find that non-program institutional trades and individual trades have predictive power for next-day returns. Although similar in nature to the research presented in Chapter 5 of this dissertation, the focus of their paper is on daily returns and dynamics, whereas the focus here is on high-frequency intra-day price and liquidity dynamics. The models and data used herein allows

[4]Joel Hasbrouck is thanked for the SAS code posted to his web site that was adapted for the price discovery analysis

a separation into two distinct groups *human* and *algorithmic*, thus allowing for a different analysis.

2.4 Liquidity and Price Discovery

In her 2003 American Finance Association presidential address (O'Hara (2003)), Maureen O'Hara highlights the interconnection between liquidity and price discovery. She makes clear, in a realistic setting where information is not symmetric across participants, that liquidity has an effect on price discovery and that both affect asset prices. The exact relationship becomes clear in the following excerpt from the speech:

> "Assets trade in markets, markets provide liquidity and price discovery, and asset prices are influenced by the transaction costs of liquidity and the risks of price discovery.[5]"

The excerpt highlights some of the functions of a market, namely to provide liquidity and price discovery, and also illustrates how both may effect asset prices. It is exactly this relationship that is studied throughout this dissertation. The importance of understanding the whole relationship is demonstrated (i.e. the effect of information on liquidity and vice versa), in focussing on how technology at securities exchanges and financial institutions have impacted liquidity supply and demand and information processing.

Liquidity and price discovery are particularly inter-related in limit order markets, where the distinction between liquidity supply and demand become blurry (Parlour and Seppi (2008)). Earlier models of liquidity supply assumed that market-makers are uninformed (Glosten and Milgrom (1985)), whereas recent research has called this assumption into question (Kaniel and Liu (2006)). Informed traders are not

[5]Source: Page 1349 of O'Hara (2003).

only placing market orders, they are also strategically placing limit orders to exploit their information.

The distinction between public and private information has also been called into question (Hasbrouck and Saar (2009)). In a recent working paper Hasbrouck and Saar (2009) noted that:

> "Virtually all private information is advance knowledge of public information.[6]"

This highlights the fact that the previous methods of disentangling public (quote-related) from private (trade-related) information may simply be capturing two facets of the same process - namely informed traders exploiting their information in both liquidity supply and demand activities. By studying a group of traders (AT) presumed to be informed and known to be fast, some important questions can be answered.

[6] Source: Slide 11 in http://pages.stern.nyu.edu/ jhasbrou/Miscellaneous/LatencyShow02.pdf

Chapter 3

Institutional Details

This chapter presents the institutional details required to interpret and understand the results attained. A overview of the Deutsche Boerse as an exchange is presented. The details of the electronic trading system Xetra is dealt with in detail and an overview of the trading day on Xetra is provided. The automated trading section provides detail and insight into the fee rebate program for algorithmic traders. Finally, data matching and other data issues are presented.

3.1 Deutsche Boerse

The DB is one of the largest securities market operators in Europe[1]. The DB is based in Frankfurt and was founded as a joint stock company in 1992. Three of the most important German securities exchanges are owned and operated by the DB. The DB operates the largest electronic trading system in Germany (Xetra), the largest face-to-face trading venue (Frankfurter Wertpapier Boerse - FWB) and one of Europe's largest derivatives exchanges (Eurex). The DB also operates a pan-European clearing and settlement system - Clearstream. Xetra and the FWB hold the dominant position in German equities trading. DAX futures, options and

[1]The Federation of European Securities Exchanges 2008 annual report listed the DB as number three in market capitalization in Europe, behind the London Stock Exchange and NYSE - Euronext.

single stock options and futures trade exclusively on the Eurex. In addition to equity futures, most money market (Euribor) and German government bond futures (Bund, Schatz, and Bobl) are traded on Eurex.

3.1.1 Xetra

The Xetra ("Exchange Electronic Trading") system is the electronic cash market stock trading system operated by DB. The Xetra system was originally introduced in 1997 and was the first fully-electronic stock exchange in Germany. Currently Xetra handles 97%[2] of German equity trading by volume. Trading begins at 9:00 am and ends with a closing call auction at 5:30 pm. The prices on Xetra are used to calculate the DAX ("Deutscher Aktien Index"), which is the leading German stock index.

Xetra is organized as a centralized limit order book. Incoming orders are compared to existing orders stored in the book. If the price of the incoming order crosses the price of an existing order they are matched. Xetra follows a price and time priority matching rule meaning that orders are matched first based on price and then on time. As an example: given two limit orders with the same direction (sell or buy) and price but different submission times, the order with the lower submission time (i.e. the oldest of the two orders) will be executed to its entire quantity before any quantity of the second order is executed.

Xetra is a completely electronic trading system accessible worldwide. Xetra members are based mostly in Germany but there are a large number of foreign members based in the UK, France, and elsewhere. Presently there are over 260 participanting banks and financial institutions from over 19 countries and more than $2,600$ authorized traders. The DB admits participants wishing to trade on Xetra based on regulations set and monitored by German and European financial regulators. After being admitted, participants can only connect electronically to

[2]See Deutsche Borse Annual Report 2007

Xetra; floor trading is operated separately with no interaction between the two trading segments.

The Xetra trading day is split into phases as follows:

- Opening call auction with a random ending that opens trading at 9:00 AM
- A continuous trading period
- A two-minute intra-day call auction at 1:00 PM with a random ending
- A second continuous trading period
- A closing call auction from 5:30 PM to 5:35 PM with a random ending

The trading phases and the ordering are similar to those found on NYSE, NYSE - Euronext and the LSE. One differentiating feature is the random ending of the call auctions, to discourage manipulation of auction prices. This trading feature is unique to Xetra but is not relevant to the remaining analyses.

The following focuses on trade occurring during the two continuous trading periods. These periods make up more the 95% (time) of the trading day. Liquidity in DAX-30 stocks is provided by public limit orders displayed in the order book for each stock. Orders execute automatically when an incoming market, or marketable limit order, crosses with an outstanding limit order. Order execution preference is determined using price-time priorities. Three types of orders are permitted — limit, market and iceberg orders. Iceberg orders are orders that display only a portion of the total size of an order. Iceberg orders sacrifice time priority on the non-displayed portion. Pre-trade transparency includes the 10 best bids and ask prices and quantities but not the ID of the submitting participant (as on the Paris Bourse (Venkataraman (2001)). Trade price and size are disseminated immediately to all participants. The tick size for most stocks is 1 euro cent with the exception of two stocks that trade in tenths of a cent.[3]

[3]Both stocks, Deutsche Telekom AG and Infineon AG have trade prices below 15 euros. The sample period overlaps a Deutsche Boerse tick-size test that was subsequently extended to other stocks.

3.1.2 Xetra as a Trading System

Xetra is not only an electronic exchange used to trade blue chip German stocks but is also the underlying trading system used by the Irish, Vienna, and Budapest stock exchanges as well as the Eurex derivatives exchange. The Xetra system supports a number of trading *modi*, including continuous double auctions, call auctions, and bi-lateral trading. Trading on Xetra can also be performed via designated sponsors as described in Klar and van den Bongard (2008). In fact, trading can be supported by more than one designated sponsor, similar to the Euronext system described in detail in Menkveld and Wang (2008).

Xetra supports a number of access options and is quite flexible in terms of functionality. Xetra can be accessed via the Internet, leased lines, or both. Traders access Xetra using a proprietary interface (Values API) or via the FIX trading protocol bridge. Participants can also use a Java-based trading application called Xetra J-Trader to trade directly on Xetra.

3.1.3 Frankfurt Wertpapier Boerse

The FWB is organized as a traditional floor exchange. Each stock traded on the floor is associated with a lead broker. Orders routed to the floor are routed directly into limit order books managed by the lead brokers. Floor trading begins at 9:00 and ends at 10:00 PM. Trading is organized as a single continuous trading phase which is always supported by a market-maker. As the relevance of floor trading has fallen, most trades are being executed on Xetra in the public order book, sometimes however large trades are still executed on the FWB.

3.1.4 Deutsche Boerse's Automated Trading Program

Xetra has a 97% market share of German equities trading. With such a dominant position, the competition authorities (Bundeskartellamt) must approve all fee changes prior to implementation. Fee changes must meet the following criteria: (i) all participants are treated equally; (ii) changes must have a cost-related justification; and (iii) fee changes are transparent and accessible to all participants. Criterion (i) and (iii) ensure a level playing field for all members and are comparable to regulations in the rest of Europe and North America. The second criteria is the most important for the current analysis. Only AT are viewed as satisfying the cost justification for the change, so DB could offer lower trading fees specifically for AT.

In December of 2007, the DB introduced its Automated Trading Program (ATP) to increase the volume of automated trading on Xetra. See Appendix A for a copy of the current ATP registration form and details of the program. To qualify for the ATP, an electronic system must determine the price, quantity, and submission time for orders. In addition, the DB ATP agreement requires that: (i) the electronic system must generate buy and sell orders independently using a specific program and data; (ii) the generated orders must be channeled directly into the Xetra system; and (iii) the exchange fees or the fees charged by the ATP member to its clients must be directly considered by the electronic system when determining the order parameters.

Before being admitted to the ATP, participants must submit a high-level overview of the electronic trading strategies they plan to employ. The level of disclosure required here is intended to be low enough to not require ATP participants to reveal important details of their trading strategies, but enough to gauge the veracity of the application for an ATP justified fee rebate. Following admission to the ATP, the orders generated by each participant are audited monthly for plausibility. If the order patterns generated do not match those implied by the strategies submitted by a participant, or are considered likely to have been generated manually, the participant will be terminated from the ATP and may also be suspended from trading on Xetra. Conversations between the author and DB revealed that a small portion of ATP eligible orders may not be included in the data set. The suspicion on the part of the DB is due to the uncommonly high number or orders to executions (message traffic) of certain participants which is typical of AT. Further discussion revealed that these participants make up less than 1% of trades in total and would therefore have no effect on the results. The ATP agreement and the auditing process ensure that most, if not all, of the orders submitted by an ATP participant are electronically generated and that most, if not all, electronically generated orders are included in the data.

The DB only charges fees for executed trades and not for submitted orders. The rebate for ATP participants can be significant. The rebates are designed to increase with the total trade volume per month. Rebates are up to a maximum of 60% for monthly volume above 30 billion Euros. The first Euro volume rebate level begins at a 250 million Euro volume and is 7.5%.

For an ATP participant with 1.9 billion euros in eligible volume, percentage rebates are calculated as follows (volumes are in millions of euros):

$$(250 * 0\% + 250 * 7.5\% + 500 * 15.0\% + 900 * 22.5\%)/1,900 = 15.6\% \qquad (3.1)$$

In the example above, an ATP participant would receive a rebate of 15.6%. A 15.6% discount translates into roughly 14,000 Euros in trading cost savings on 91,200 in total, and an additional 5,323 Euros savings on 61,500 in total in clearing and settlement costs. This rebate (14,000 + 5,323) translates into a 0.1 basis point saving of the 1.9 billion in turnover. For high-frequency trading firms whose turnover is much higher than the amount of capital invested, the savings are significant. See Table 3.1 for an overview of the ATP rebate levels by volume levels.

The fee rebate for ATP participants is the sole difference in how orders are treated. AT orders are not displayed differently in the publicly disseminated Xetra limit order book. The Xetra matching engine does not distinguish between AT and

Table 3.1: ATP-Rebate Program: Rebate table for ATP participants at volume levels.

Cumulative Monthly ATP-Volume (in Mil. Euros)	ATP-Rebate (per Volume level)
$0 < 250$	0.0%
$250 < 500$	7.5%
$500 < 1000$	15.0%
$1000 < 2000$	22.5%
$2000 < 3750$	30.0%
$3750 < 7500$	37.5%
$7500 < 15000$	45.0%
$15000 < 30000$	52.5%
> 30000	60.0%

human orders. Therefore, there are no drawbacks for an AT firm to become an ATP participant. Thus, it is expected that all algorithmic traders take advantage of the lower fees by joining the ATP. From this point on, ATP participants are equated with algorithmic traders and use AT to describe both. Non-ATP trades and orders are assumed human or human generated.

3.2 Data and Data Providers

The data for the following analyses were acquired from a number of sources, both public and proprietary. The bulk of the data is accessed using the TAQTIC data service operated by SIRCA on behalf of Reuters. System order data generated by ATP participants was provided by the Deutsche Boerse. Market capitalization and other firm-specific data (stock splits, mergers, and other capital actions) were collected from the Deutsche Boerse and individual firm websites.

The TAQTIC - SIRCA data provides access to ultra-high (tick-by-tick) frequency market microstructure data. Market microstructure data is delivered in two separate files. One file (trade file) contains a record of all trades and the best bid and ask quote throughout the trading day. The second file (order-book file) contains a record of the best 10 bids and asks for a given security. The trades in the trade file are stored with a Reuters Identification Code (RIC) that uniquely identifies a security and trading venue, trade price, volume, prevailing bid and ask prices, and qualifier. The qualifier field stores relevant market conditions (open, close, maximum, minimum, volatility interruption, etc.), trading phase, and in some cases, the trading program (Crossing or Xetra Best). The best bid and ask quote records contain RIC, bid and ask, prices and volumes, number of participants on each side (bid/ask), qualifiers and time-stamps. The order-book file contains the same information as for the best bids and asks in the trade file for the entire order book (i.e. 10 levels). This data allows for an almost complete reconstruction of the trading day on Xetra.

The DB provided access to ATP system order data. The system order stores the entire order history generated by ATP participants. The system order data is proprietary to the DB and not distributed to data providers, including SIRCA. The data records each individual order (entry, modification, execution and deletion) submitted by an ATP participant. The data includes an order entry and modification date and time-stamp, order type, limit or execution price and volume. Using this data and the SIRCA public data the market can be recreated and broken down into AT and human generated order flow. These data are the basis for the results attained in the following chapters.

Chapter 4

Latency, Liquidity and Algorithmic Trading

On April 23rd, 2007, the Deutsche Boerse made the most important upgrade to their trading system since 2002 by introducing Xetra 8.0. The new release of Xetra reduced average system latency from 50 ms to 10 ms round trip. Trading costs decreased by between 1 and 4 basis points. The liquidity increase is the result of lower adverse selection costs that are only partially translated into higher liquidity. This is interpreted as a decrease in the competition between liquidity suppliers, and specifically between liquidity suppliers employing high-frequency trading strategies (such as algorithmic traders) and those not using such technologies. Trade correlated information fell dramatically, post-upgrade. Price discovery shifted from being predominantly trade-correlated (private) to predominantly quote-correlated (public). Together these findings are evidence of the positive (liquidity increasing) impact of latency on liquidity and price discovery in an electronic limit or market.

4.1 Introduction and Literature Review

With the advent of fully electronic trading (Jain (2005)), the IT-systems used by exchanges to match and report orders are becoming increasingly important. Investors are increasingly using technology to translate their investment decisions into orders. This increased use of technology has also driven an unprecedented increase in the number of orders per trade (Hendershott, Jones, and Menkveld (2008)), volume (Chordia, Roll, and Subrahmanyam (2007)), and the number of transactions. These two trends in securities trading have increased the strain on the exchange systems used to match and report trades. This increase in system capacity and AT can have a number of effects on liquidity and information, all of which are either unknown or disputed. These effects are studied in the following.

As more investors are using technology to mange their orders, exchange systems can come under great stress. An unfortunate example of this is the recent London Stock Exchange (LSE) system failure[1] that caused trading to cease for seven hours. This system failure, caused by a flood of orders in response to the Freddie Mac and Fannie Mae bailouts, makes painfully clear the importance of IT-systems to the operation of financial exchanges worldwide. In response to increases in algorithmic and quantitative trading, exchanges[2] have been upgrading their infrastructure to reduce system latency. This, in turn, increases the number of orders that can be handled per unit of time. Exchanges have touted the liquidity-improving effects of reducing system latency. In this chapter the hypothesis that reducing system latency increases liquidity is tested. The equally important question as to how this affects the processing of market information is also addressed.

Latency is critical in electronic trading! Trading strategies that rely on short-term relative price differentials, such as index arbitrage or correlated-pair trading, require near-simultaneous execution and furthermore face execution risks directly related to changes in latency. In addition, if some traders receive pricing relevant information before others, then the former can exercise the free-trading option offered by slower investors (Copeland and Galai (1983)). Latency may therefore affect

[1]See September 10, 2008 Wall Street Journal - Back Online, LSE Faces Skeptics

[2]Deutsche Boerse rolled out their Xetra 8 system on April 23rd, 2007, the London Stock Exchange in June of 2007, the New York Stock Exchange staggered during Q4 2006 and Q1 2007, and the Toronto Stock Exchange rolled out Quantum in December of 2007

the compensation liquidity suppliers require for the free trading option they supply. While the effect of latency on liquidity is unclear, what is clear is that decreasing latency changes the competitive factors in the demand and supply of liquidity and how quotes are updated to reflect public information.

Latency is commonly defined as the amount of time it takes for a trader to receive feedback about a submitted order. Using the example of a marketable buy order, latency is the amount of time that elapses between submitting the order and receiving confirmation that the order executed at a given quantity and price. Latency in an electronic-order-driven market, in contrast to market-maker markets, is determined entirely by the IT-systems and algorithms supporting the operations of an exchange. In market-maker markets, or market-maker segments in hybrid markets, latency is a function of the IT-systems routing an order to the floor and the time it takes for a human to process the order.

This is the first known study to isolate the effect of latency on liquidity and information processing in an electronic limit order market. The natural experimental framework afforded by the April 23rd, 2007 Xetra 8.0 upgrade is used to test the hypothesis that reducing latency impacts liquidity and information processing. The Xetra 8.0 upgrade is unique in that a number of system changes were made simultaneously with the sole purpose of reducing latency. The upgrade included no market model or other microstructure changes other than the latency-reducing system upgrade.

A panel-estimation technique is used to test for changes in liquidity. The results show that a reduction in latency has a positive effect on liquidity, thus demonstrating an inverse relationship. The results hold across market capitalization (Mcap) quartiles (Q1, Q2, Q3, and Q4) and trade sizes. Interestingly, the increase in liquidity is driven by a reduction in the adverse selection component of spreads - which falls dramatically. The analysis is conducted using a VAR framework as in Hasbrouck (1991a) and Hasbrouck (1991b). The permanent price impact per trade falls from roughly 3 basis points (bps) on average to 0.6 bps for large stocks. Quotes have also become more informative with an increase in the total amount of information attributable to quote changes increasing from roughly 40% to 90%. This reduction in adverse selection costs translates into a comparatively small liquidity increase. As in Hendershott, Jones, and Menkveld (2008), this is interpreted as a change in the competitive landscape where those with the best algorithms extract most of the surplus.

Only recently have researchers begun to focus on the effects of AT on market outcomes. Until recently, little data was available on AT activity. Two recent studies (Chaboud et al. (2009) and Hendershott and Riordan (2009)) are the first to have access to detailed AT data. Chaboud et al. (2009) study the effects of AT in foreign exchange (FX) markets using three widely-traded currency pairs. Two of their findings are interesting: they find that AT is not related to volatility and that the variance in FX returns is not related to AT order flow. Although no direct evidence is found on average AT versus human information in this study, the findings indicate that the relationship between trade-correlated and trade-uncorrelated information changes dramatically. This finding highlights the increase in public information processing post-upgrade due to a reduction in latency. Hendershott and Riordan (2009) study AT trades and orders in DAX stocks and find AT to be both more informed and greater suppliers of liquidity than humans.

The results contrast somewhat with both earlier (Demsetz (1968)) and more recent (Bacidore, Ross, and Sofianos (2003), Battalio, Hatch, and Jennings (2003), Bennett and Wei (2006) empirical studies of transaction costs, as well as Boehmer (2005)), that find a trade-off between speed and cost. Boehmer (2005) states that there is a trade-off between costs and speed that is robust over time and insensitive to the econometric specification. The primary difference between these studies and the current one is that herein the effect of a system-wide latency reduction is studied. The previous studies are in effect studying two similar but unrelated effects.

The question of execution speed involves both a microstructure and an infrastructure component. Using the example of a market versus a limit order, a market order executes faster than does a limit order, but pays the spread. A limit order takes longer to execute but receives the spread. Although there is a time component, it is not the driving factor. A limit order takes longer to execute but does not necessarily cost less as the order execution time increases. In fact, there is no relationship between the waiting time of two equivalent limit orders and the execution costs. Bacidore, Ross, and Sofianos (2003) address exactly this issue in their analysis of guaranteed and non-guaranteed orders. A guaranteed order waits on average 251.1 seconds for execution and costs 17 cents. A non-guaranteed order costs only 7 cents but executes in under $17 seconds$. The same study also notes that this difference in time to execution is the time it takes for the order to interact with the floor trader. The electronic transit time was roughly 6.3 seconds in their sample. This example highlights two components of latency. The first is a microstructure one, like waiting for the floor to interact with an order. The second is an infrastructure effect and the focus of this work. The findings in no way contradict these previous studies. Rather they represent the study of two similar but distinct questions.

The literature also shows that traders unambiguously prefer fast execution to slower execution when holding costs and other factors equal. Blume (2002) cites a survey from 2000 from Sanford and Bernstein where 58% of online investors state that:

> "...immediacy of execution is more important than a favorable price.[3]"

Huang (2002) finds that the timeliness of information reflected in quotes is an important issue and that electronic communications networks (ECN) quotes are more informative because of the speed with which they reflect information. They equate the speed of the trading system with the informativeness of quotes. Clearly there are clientele that prefer fast execution and are willing to pay for it. Using arbitrage

[3]Weekly Notes. Bernstein Research (New York: Sanford C.Bernstein & Co., Inc., May 12, 2000).

trades as a concrete example, the trade-off between execution costs and speed is actually a tradeoff between execution risk and profit. If the profit is minimally affected but the execution risk lowered, these traders are more likely to prefer faster execution. They will also be more likely to trade even when the per-trade profit is small.

Copeland and Galai (1983) made an important contribution in the understanding of trading risks, specifically liquidity supply. They formulated one of the key costs incurred by liquidity suppliers, something they called the 'free-trading option'. The free-trading option is the option a liquidity supplier, or market-maker, supplies to the market when they provide firm commitments to trade. Both quotes and limit orders are firm commitments to trade and are exposed to free-trading option risk. For a liquidity supplier, the free-trading option is a cost which increases with time. The longer the option is exposed to the market, the higher is its value. In the hypothesis development section of this dissertation, it is shown that by reducing the duration of the free-trading option (which is comparable to lowering latency), the cost to a liquidity supplier of the free-trading option can be lowered. This is the only market microstructure framework with an explicit mechanism for latency.

Theoretical studies on limit order markets (Cespa and Foucault (2008), Foucault, Kadan, and Kandel (2005), and Parlour (1998)) make some assumptions about the timeliness and speed of trade. They assume that an increase in speed also causes an increase in the informational efficiency of prices (Cespa and Foucault (2008)). Further, they assume that faster trade means higher cost, although this assumption is attributed to market microstructure (limit vs. market order) rather than to a direct market latency effect.

A study that is similar in nature to the current one is the Hendershott and Moulton (2007) study on the effect of the introduction of the New York Stock Exchange's (NYSE) Hybrid system. While similar in theory to this study, it differs in that the NYSE not only increased execution speed by offering automated execution for orders above 1,099 shares, but also simultaneously made changes to the market structure. Pre-hybrid automatic execution in a limit order environment is only available to orders under a volume 1,099 while post-upgrade orders can be automatically executed up to 1,000,000 thereby circumventing the NYSE specialist. These results differ in that the previous studies find an increase in both quoted and effective spread, whereas here only a decrease in the effective spread is found. Hendershott and Moulton (2007) attribute the increase to higher adverse selection costs as a result of anonymous trading.

Another recent study by Easley, Hendershott, and Ramadorai (2007) looks at the effect of a latency reduction at the NYSE in 1983. The results are interesting in that they find an increase in the price of stocks that switch from higher latency trading to lower latency trading. They also find a reduction in transaction costs of 13 basis points after the switch from higher to lower latency. The current study is somewhat different in that the focus is on studying an exclusively technological change at DB with no accompanying market model or microstructure changes. Another differentiating factor is the trading era. In 1983, investors traded almost exclusively manually whereas in 2007 roughly 39% of trade was algorithmically generated on Xetra[4].

White and Frame (2004) studies financial innovation and reports far too few empirical studies of financial innovation and analysis of its impact. By studying an exchange system upgrade in a period of increased algorithmic trading, the current focus is on the study of two parallel innovations and their interaction.

4.2 Xetra 8.0

The release of DB's Xetra system on April 23rd, 2007 and the effects thereof are the subject of this chapter. Xetra 8.0 was the first major system upgrade since the Xetra 7.0 release on August 20th, 2002. The release of version 8.0 is interesting in that it provides an ideal opportunity to study the effect of trading system latency,

[4]See the 2007 Deutsche Boerse Annual Report p. 81

or speed, in isolation. DB introduced no market model changes, different execution mechanisms, or new order types. They made a series of system upgrades with the sole purpose of reducing the latency of the Xetra trading system.

The new Xetra trading system is designed to reduce the trading system latency from a minimum of 40 milliseconds to a minimum of 10 milliseconds. The most important upgrade was to the trade matching algorithm and system used to match incoming orders. Previously, each incoming order was stored by the matching algorithm on the physical hard-drive before being matched and reported. Post upgrade, each order is matched in 'virtual' memory, saving the computationally expensive operation of storing each order on a physical drive before matching. Other important upgrades include an increase in network bandwidth to members and an internal network upgrade.

The most important feature of the upgrade was the reduction in market latency. The time between order entry and confirmation was reduced from 55 millisecond to an average of 13 milliseconds for 'speed-sensitive' traders. The following is a list of the most important upgrades:

- split market data streams
- improved caching
- memory-based order matching
- increased network capacity

Each improvement focuses on a specific latency problem. Splitting market data streams avoids data bottlenecks that arise when market participants are forced to receive every order book update for each Xetra security. The new system allows participants to select the market segments for which they wish to receive order book data. Caching further improves the speed of the trade matching algorithm as does memory-based order matching. DB also dramatically improved their network capacity to deal with the increase in data and communications network requirements.

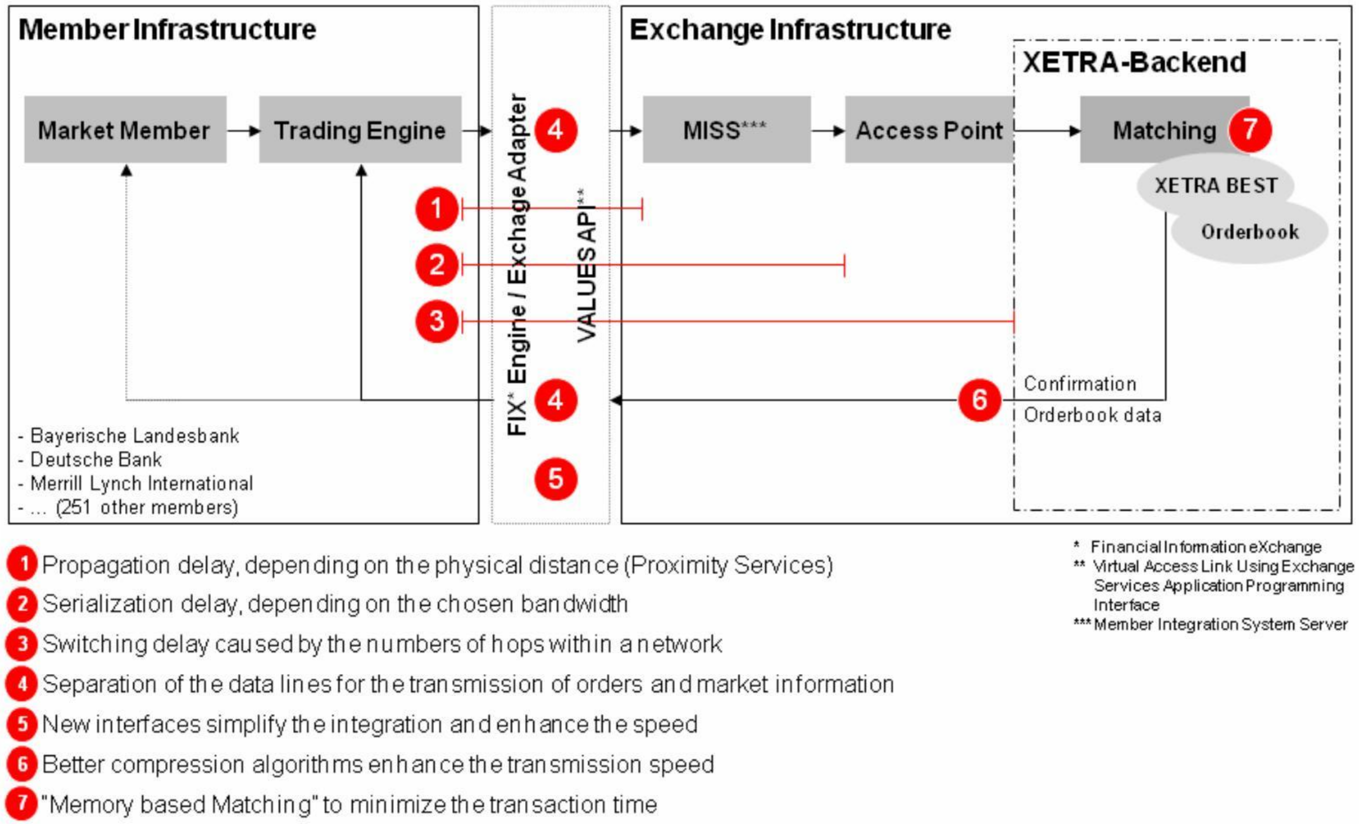

Figure 4.1: Xetra Latency Reducing Upgrades: This figure illustrates the latency reducing upgrades to Xetra.

See Figure 4.1 for a diagram depicting the latency relevant changes made to the Xetra system.

4.2.1 Algorithmic Trading on Xetra

The Xetra 8.0 release was targeted directly at reducing latency with the goal of increasing algorithmic trading. Recent research (Hendershott, Jones, and Menkveld (2008)) presents the effects on liquidity of a latency reduction. Exchanges themselves promote latency reduction and the resulting increase in algorithmic trade as positive for liquidity, which is confirmed in Hendershott, Jones, and Menkveld (2008). In Q1, DB reported[5] that 45% of trades in their own stock were executed by algorithmic traders, up from 37% for the full year 2007. Liquidity has undoubtedly increased on Xetra, and worldwide (Chordia, Roll, and Subrahmanyam (2007)), but whether a causal relationship exists between algorithmic trading, latency and liquidity is an open question.

To encourage automated trading, DB introduced the 'Automated Trading Program' (ATP) in December of 2006. The ATP program reduces the explicit trading costs for participants' orders that meet two of three conditions. The ATP agreement (see Appendix A) stipulates that price, time of order submission, and/or quantity decision must be made by an algorithm or computer program. The costs are adjusted based on total order flow for a given month; discounts begin at a minimum of $250 million euros of executed volume. Data generated by participants of this program are analyzed in the following chapter .

4.3 Hypothesis Development

The literature is unclear as to the effect of reducing latency on liquidity and information. Theoretically, the model that best fits the real world scenario is the Copeland

[5]http://www.reuters.com/article/companyNews/idUSWEB425820080507

and Galai (1983) model. They introduce a method to value firm commitments to trade at the posted bid and ask prices as options. Although not the main purpose of the model, they introduce a method to determine a theoretical impact of latency on liquidity. In their options valuation framework, they allow for an effect of the duration of quotes on the value of the option provided. As with most options, they increase in value with increased duration. In the current context, lowering the minimum amount of time it takes to revise or delete an order is the same as reducing the duration of the free-trading option. The current analysis is designed to present a stylized impact of latency reduction on liquidity and specifically the supply thereof. By no means should the results of the analysis at the ten, five, and two minute frequencies be interpreted as representative of the absolute value of changes in option value at millisecond durations.

The original model settings are used but calculated for different latencies using a constant volatility. The idea is to get a feel for the sensitivity of the value of the free-trading option to a reduction in latency. The value of a European call option is reported in Table 4.1 below, with an annualized volatility of 20% with latencies of ten, five and two minutes and stock price of 100 and ask prices in 1*ct* increments from 100.01 to 100.10. The value of the options in the table below show the average cost incurred by a liquidity provider when submitting a sell order on a stock at a given ask price that has a duration of two, five, and ten minutes.
The results in table 4.1 show the dramatic drop in value of the free-trading option with a decrease in duration. Decreasing the duration by half (from ten to five minutes) causes a drop of 30% in the value of the free-trading option. The framework does not allow any inferences to be made with regards to the absolute value of the trading option. But it certainly lends support to the hypothesis that by lowering latency, a relatively large increase in liquidity may result, all else equal. From this, one of the central hypotheses of this paper is derived:

$H1_0$: A system-wide reduction in latency will have a positive

Table 4.1: Hypothesis Development: The table data are calculated using the Copeland and Galai (1983) option framework. The first column are ask prices, the following three columns are call option values for a stock price $S_0 = 0$ of 100, an annualized volatility of 20%, ask prices as in the first column and durations of 2, 5 and 10 minutes. The last three columns are percentages that decrease when latency is decreased from 5 to 2 minutes, 10 to 5 minutes, and 10 to 2 minutes.

	Time in Minutes			% Decrease		
Ask Price	2	5	10	5 to 2	10 to 5	10 to 2
100.01	0.034	0.057	0.083	39.75%	30.98%	58.42%
100.02	0.030	0.053	0.078	42.82%	32.71%	61.52%
100.03	0.026	0.048	0.074	45.93%	34.48%	64.57%
100.04	0.022	0.044	0.069	49.08%	36.28%	67.55%
100.05	0.019	0.040	0.065	52.23%	38.11%	70.44%
100.06	0.016	0.037	0.061	55.38%	39.97%	73.21%
100.07	0.014	0.033	0.057	58.50%	41.85%	75.87%
100.08	0.012	0.030	0.054	61.56%	43.75%	78.38%
100.09	0.010	0.027	0.050	64.56%	45.66%	80.74%
100.10	0.008	0.025	0.047	67.48%	47.58%	82.95%

effect on liquidity.

Hypothesis 1 formalizes the relationship between latency and liquidity. The Copeland and Galai (1983) model provides a theoretical lower bound on the liquidity improvement. By halving latency, the maximum liquidity increase is between 30% and 50% depending on the distance of the ask from the stock price. The central assumption in hypothesis 1 is that some liquidity suppliers are in fact speed-sensitive. If liquidity suppliers do not have systems in place to exploit the new exchange systems, they may in fact reduce liquidity to compensate for the increased risk of being picked off. The mechanism by which liquidity increases is not specifically determined but is joint with the following hypothesis:

$H2_0$: **The informativeness of quoted prices increases with speed.**

As market speed increases, or latency decreases, the informativeness of prices will increase (cf. Foucault, Roëll, and Sandas (2003)). Several studies (Barclay, Hendershott, and McCormick (2003b) and Huang (2002)) have shown that faster markets generate more efficient prices than do slower markets. It would appear reasonable to assume that this finding holds when a single market increases its speed.

4.4 Data and Sample Selection

Data from the TAQTIC data service operated by SIRCA on behalf of Reuters as described in detail in 3 is used. Data on market capitalization is collected directly from the DB web site, company annual reports, and is compared with other public data sources (Yahoo! Finance, Google Finance, and OnVista). The sample period covers the 40 trading days prior to and post April 23rd, 2007 - the event date. This leaves a sample period between February 22nd, 2007 and June 19th, 2007. This period is selected because it allows allows an analysis of the short-term and long-term changes around the event.

4.4.1 Data Source

Data is retrieved directly from the Securities Industry Research Centre of Asia-Pacific (SIRCA)[6] on behalf of Reuters'. SIRCA provides trade, order, quote, and order book data for a large number of stocks trading on exchanges worldwide. Specifically, trades, best bids, and best asks are retrieved for the stocks in the original sample. Each trade and quote is time-stamped to the millisecond and accessible via Reuters Instrument Code (RIC). All prices are reported in Euros. The 110 stocks that made up the HDAX, as reported by TAQTIC (the data access tool provided by SIRCA) as of February 22nd, 2007, are used as the sample.

The first and last five minutes of the trading day are removed to avoid biases associated with the information processing and inventory management processes at those times. The data spans trading between 9:05 am and 5:25 pm local time with some exceptions, as specified in the following. Xetra features intra-day auctions and

[6] `http://www.sirca.org.au/`

volatility interruptions which halt continuous trading. The analysis is focused on continuous trading so all data recorded outside these hours and during volatility interruptions are deleted. The opening, closing, and intra-day and volatility interruptions are identified via Reuters' qualifying code attached to special types of trades and period of time in a trading day. These qualifiers are used to filter the data.

To further validate the results and compensate for potential time trends, Xetra trades and quotes are matched with Frankfurter Wertpapier Borse (FWB) trades and quotes. Since the stocks traded on Xetra and FWB are the same, this should compensate for any time trends in the variables. The differenced ($Xetra_{Variable} - FWB_{Variable}$) variables should be independent of these.
See Figure 4.2 for a graph of the natural logarithm of volumes over the sample period. The figure shows that volume does not shift as a result of the Xetra upgrade and confirms the robustness of both the Xetra and Xetra-FWB instruments to this effect.

4.4.2 Sample Selection

The sample contains the 110 stocks that make up the DB's HDAX. The HDAX is a combination of three main indexes: the DAX, TecDAX, and MDAX[7]. They are the most actively traded and highest quality publicly traded German companies and represent a broad cross-section of industries. The DAX contains the 30 largest and highest quality German blue-chip stocks determined by market capitalization, free-float, transparency regulations, and industry. The MDAX is made up of the next largest 50 companies, followed by the 30 technology stocks in the TecDAX. The index composition as of 22 February 2007 is taken. This is well before the Xetra 8.0 upgrade. All members of the HDAX meet certain minimum admission requirements, viz: they must publish quarterly reports, adhere to IFRS or US-GAAP accounting

[7]See: Deutsche Boerse web site for a full description of the indexes

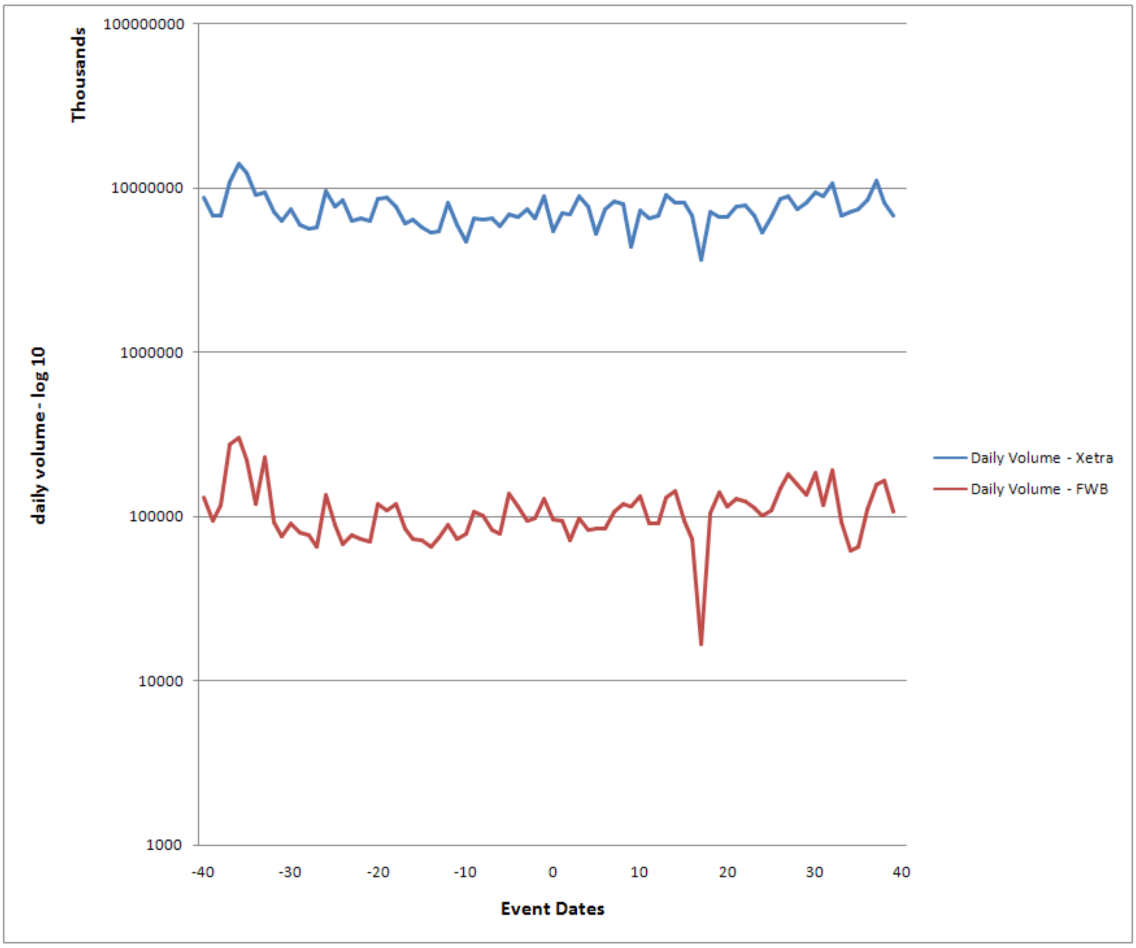

Figure 4.2: Daily Volume: Xetra and FWB: This figure graphs the daily log euro volume from the Frankfurt floor and Xetra markets. The event dates are on the x-axis and the daily log euro volume on the y-axis.

standards, publish a financial calendar, hold one analyst conference per year, and provide ad-hoc disclosure information in German and English.

Stocks that do not meet certain criteria are removed. This removal avoids effects related to size, trading frequency, and price. Criteria, modified to our sample from Hendershott and Moulton (2007), were used to prepare the data. A stock must have traded above 1 euro and below 500 euros during the entire sample period. A stock must have been traded continuously throughout the study period and traded at least twice a day. Stocks that split or were de-listed during the observation period were removed from the sample data. Stocks that were dropped from the HDAX during the sample period were also removed. The final sample consists of 101 stocks. Table

Table 4.2: Descriptive Statistics for Xetra and the Frankfurt floor (FWB): The sample consists of stocks listed in Deutsche Börse's HDAX segment. The observation period comprises of 40 trading days before and after the introduction of Xetra 8 on 23 April 2007. Table 4.2 Panel A reports descriptive statistics for Xetra and Panel B reports statistics for the Frankfurt floor. Average measures are calculated on tick data. Daily turnover per instrument and daily trade count per instrument are calculated on a daily per instrument basis. Market capitalization is calculated as the product of shares outstanding and the average price. All spread measures are reported as relative measures in basis points. All monetary measures are reported in Euros.

Panel A: Descriptive Statistics Xetra				
	Mean	Std. Dev.	Min.	Max.
Shares (1000)	234,690	490,060	6,350	436,130
Market Cap (MEUR)	10,584	17,277	356	80,236
Price (per Trade)	70.98	47.34	3.16	351.70
Quoted Spread	12.36	15.00	> 0.00	820.94
Effective Spread	7.50	10.14	> 0.00	581.24
Realized Spread	1.92	444.67	3992.34	997.35
Price Impact	5.58	44.49	-993.50	999.64
Turnover (1000 EUR)	71,816	153,330	48	2,718,500
Trade Count	1,492	1,868	9	20,467
Per Trade Turnover	48,150	94,650	3	22,055,446

Panel B: Descriptive Statistics FWB				
	Mean	Std. Dev.	Min.	Max.
Shares (1000)	234,690	490,060	6,350	436,130
Market Cap (MEUR)	10,584	17,277	356	80,236
Price (per Trade)	58.13	43.72	3.17	351.00
Quoted Spread	15.62	18.79	> 0.00	982.57
Effective Spread	6.81	12.24	> 0.00	841.68
Realized Spread	4.82	48.09	-985.88	1000.00
Price Impact	1.99	47.53	-924.86	994.46
Turnover (1000 EUR)	1,059	2,335	0.1	52,875
Trade Count	90	145	1	2,020
Per Trade Turnover	11,829	45,192	4	10,934,900

4.2 reports the average price, trades, daily turnover, and turnover per trade for all stocks in the final sample. Pre- and post-Xetra 8 variable values are reported in Table 4.3. The list of the full sample stocks with average, minimum, maximum and standard deviation of price are reported in Table 4.10 in Appendix 4.9.

4.4.3 Liquidity Measures

The now common Lee and Ready (1991) algorithm is used with contemporaneous quotes as proposed by Bessembinder (2003a) to sign trades. Bessembinder (2003a) compares different heuristics to infer trade direction with proprietary data featuring the trade direction and finds that a comparison of the trade with the contemporaneous quote using Lee and Ready's heuristic provides the best results. Given the current information technology and the period in which the data were collected, using contemporaneous quotes should not bias the results.

Several proxies for liquidity are used. One main divergence from what is presented in much of the existing literature is that, rather than calculating the half-spreads, full and round-trip spreads are presented. Quoted spreads are the easiest and most common measure of trading costs and can easily be calculated using trade and order data. All calculations presented below are spreads relative to stock price and are reported in basis points (bps). In order to avoid distorted results from ambiguity in the raw data, intra-day observations featuring a quoted spread larger than 10%, an effective spread larger than 10%, a realized spread larger than 10% or smaller than -10%, or a price impact larger than 10% or smaller than -10% are removed from the data.

The quoted spread on Xetra is created through public limit orders submitted by various participants. Let $\mathrm{Ask}_{i,t}$ be the ask price for a stock i at time t and $\mathrm{Bid}_{i,t}$ the respective bid price. If $\mathrm{Mid}_{i,t}$ denotes the mid-quote, then the quoted spread is calculated as follows:

$$\text{Quoted Spread}_{i,t} = (\mathrm{Ask}_{i,t} - \mathrm{Bid}_{i,t})/\mathrm{Mid}_{i,t}$$

The effective spread is defined as the spread paid when an incoming market order trades against a limit order. The effective spread also captures institutional features of a market, such as hidden liquidity or market depth. If $\mathrm{Price}_{i,t}$ is the execution price, then the effective spread is defined as:

$$\text{Effective Spread}_{i,t} = 2 * D_{i,t} * ((\text{Price}_{i,t} - \text{Mid}_{i,t})/\text{Mid}_{i,t})$$

$D_{i,t}$ denotes the trade direction with -1 for market sell and $+1$ for market buy orders. The realized spread measures liquidity supplier revenues which are independent of adverse selection costs imposed on the uninformed by the informed (Bessembinder and Kaufman (1997)). The realized spread is calculated using the mid-quote five minutes after the trade ($x = 5$).

$$\text{Realized Spread}_{i,t} = 2 * D_{i,t} * ((\text{Price}_{i,t} - \text{Mid}_{i,t+x})/\text{Mid}_{i,t})$$

Price impact is an approximate measure of the adverse selection component of the effective spread. The price impact is the effective spread minus the realized spread and measures the information content of a trade. It approximates the permanent impact of a trade under the assumption that information impacts are permanent and realized at the five-minute mark, whereas other effects, inventory and explicit trading costs are transitory. Following a trade, liquidity suppliers adjust their beliefs about the fundamental value of an asset depending on the information content of a trade (cf. Glosten and Milgrom (1985)). The simple price impact of a trade is calculated as follows:

$$\text{Price Impact}_{i,t} = 2 * D_{i,t} * ((\text{Mid}_{i,t+x} - \text{Mid}_{i,t})/\text{Mid}_{i,t})$$

The results are reported below. The simple price impact gives us an indication as to the information content of trades. More robust information measures are presented in the following information section.

4.4.4 Calculation

Minute-by-minute observations are aggregated to a daily frequency to capture the intra-day dynamics of each variable but avoid some of the noise associated with a higher sampling frequency (trade-by-trade or quote-by-quote). Table 4.3 reports the sample summary statistics.

Table 4.3: Liquidity and Information Pre and Post Xetra 8 for Xetra: The sample consists of stocks listed in Deutsche Boerse's HDAX segment. The observation period comprises of 40 trading days before and after the introduction of Xetra 8 on 23 April 2007. Table 4.3 reports descriptive statistics for quoted spreads, effective spreads, realized spreads, price impacts, and permanent impacts of trade innovations. Quoted spread, effective spread, realized spread, and price impact are calculated on tick data. Permanent price impact statistics are calculated using daily data. Results are reported for the entire sample and individually by a stock's market capitalization. Stocks are divided into four groups depending on their market capitalization. Market capitalization is calculated as the product of shares outstanding and the average price over the observation period for a single stock. All results are reported in basis points.

	Liquidity and Information Pre and Post Xetra 8 Introduction									
	Quoted Spread		Effective Spread		Realized Spread		Price Impact		Permanent Price Impact	
	mean	Std.Dev.	mean	Std. Dev.	mean	Std. Dev.	mean	Std. Dev.	mean (daily)	Std. Dev. (daily)
Sample										
full	12.21	15.01	7.44	10.19	1.91	44.85	5.53	44.67	2.81	2.65
pre	12.45	15.98	8.15	11.40	0.49	48.17	7.65	48.06	4.42	2.73
post	12.06	14.39	6.71	8.71	3.39	41.06	3.32	40.71	1.19	1.19
MCAP Q1										
full	6.54	6.87	4.47	4.42	1.32	35.16	3.14	35.07	1.48	1.09
pre	6.23	6.93	4.77	4.68	0.58	36.21	4.20	36.13	2.29	0.94
post	6.71	6.83	4.15	4.11	2.09	34.03	2.06	33.91	0.66	0.38
MCAP Q2										
full	14.02	13.02	9.22	9.71	1.71	51.23	7.51	50.90	2.56	2.04
pre	13.40	13.66	9.77	10.60	-0.61	54.14	10.39	53.75	4.04	1.85
post	14.45	12.55	8.65	8.66	4.13	47.89	4.52	47.56	1.08	0.69
MCAP Q3										
full	22.70	19.22	14.27	14.83	2.80	63.08	11.47	62.52	3.06	2.31
pre	21.68	19.16	15.61	16.28	-0.40	70.12	16.01	69.46	4.86	1.89
post	23.43	19.23	12.82	12.92	6.25	54.27	6.57	53.62	1.27	0.82
MCAP Q4										
full	33.56	25.78	22.51	21.99	7.95	70.15	14.56	68.98	4.17	3.73
pre	33.69	27.17	25.35	24.39	5.29	79.29	20.05	77.97	6.59	3.52
post	33.45	24.59	19.04	18.03	11.19	56.84	7.85	55.33	1.78	1.94

The time-series mean of each variable is calculated per stock. The cross-sectional means of the variables are reported in table 4.3. Trade prices on Xetra range from 3.16 euros to 351.70 euros with a sample mean of 70.98. The average stock trades 1,492 times a day which translates into roughly three times per minute. Table 4.2 shows an interesting phenomenon, *viz.* generally in order-driven markets without designated market makers, the effective spread should be greater than the quoted spread. The results show that the quoted spread is on average larger than the effective spread. This indicates that traders monitor the market and trade when spreads are lower than average. This also indicates that a great deal of order splitting occurs and that it is worthwhile to do so.

4.4.4.1 Spread Decomposition

Table 4.2 reports the descriptive statistics for the sample. Panel A reports the descriptive statistics for Xetra while Panel B gives those for the FWB. The following analysis of liquidity focuses on the differenced[8] results to mitigate any time effects in the sample. The table shows clearly that quoted spreads are smaller on Xetra while effective spreads are somewhat greater. This, coupled with a smaller price impact, leaves a large realized spread for FWB trades. These results confirm other empirical studies that find that repeated interactions, by humans, lead to lower execution costs due to an ability to avoid informed trades (Hendershott and Moulton (2007)). Other clear differences are the number of trades per day and the average turnover per trade, both considerably higher on Xetra.

Table 4.3 reports the mean and standard deviations of quoted, effective, and realized spread, the price impact, and summed daily impulse response function (trade innovation). Table 4.3 shows a decrease in measures of trading costs (quoted and effective spreads) an increase in liquidity supplier revenues, and a corresponding drop in price impact or information, post-upgrade. Most interestingly, the robust

[8] i.e $QuotedSpread_{reported} = QuotedSpread_{Xetra} - QuotedSpread_{FWB}$

information results show a decline from 4.42 bps to 1.19 bps and the results are consistent across all Mcap categories.

4.5 Liquidity Analysis

Each equation is estimated for each setting, once for Xetra alone, once on FWB values and once on the difference. The focus of the analysis is on the differenced results but the findings hold for both settings (Xetra and differenced). To test the hypothesis that reducing latency has an effect on liquidity, regressions of the following form are estimated:

$$LM_{i,t} = \alpha_i + \delta Xetra8_{i,t} + \beta VDAX_t + \epsilon_{i,t} \tag{4.1}$$

where liquidity measure (LM) is the quoted spread, effective spread, realized spread, and price impact on date t for stock i. α_i are fixed cross-sectional effects for each individual stock. $Xetra8_{i,t}$ is a dummy variable that takes the value 0 before April 23rd 2007 and 1 otherwise. A daily volatility measure $VDAX_t$ is included as in Hendershott and Moulton (2007) to control for market-wide volatility changes and the effects thereof on market-wide liquidity. For the $VDAX$, the daily opening value of DB's 3-Month $VDAX - New$ is used for each date in the sample period. Poolability tests show that data are not poolable. A fixed-effects model is used that accounts for cross-sectional differences in stocks. The panel regressions are estimated with robust standard errors for within-groups estimators (Arellano (1987)) which are essentially White's robust standard errors (White (1980)), adjusted for panel data.

The results are the same with only marginal differences in the magnitude of values when a pooled regression[9] is used. Four additional time-invariant control variables are included in the pooled regression which account for a large percentage of stock individual effects. The four control variables are: the natural logarithm

[9] $LM_{i,t} = \alpha + \delta Xetra8_{i,t} + \beta VDAX_t + \sum_{k=1}^{4} \lambda_m Control_{i,m} + \epsilon$

of the average stock price on event date 0; the log of the market capitalization; the standard deviation of returns of the sample period; and the log of the average turnover per stock. The log of the average price controls for price level effects which may be driving the results, whereas the log of market capitalization controls for firm size. The standard deviation of returns are used to control for the firm-level volatility while the log of the average turnover per stock is a control variable that captures the trading activity of a given firm. The time-invariant control variables are not included in the fixed-effects model since individual fixed-effects account for those differences.

The results of the panel regression from the fixed-effects model are shown in table 4.4 for the full sample and by market capitalization quartiles. The above fixed-effects model is also estimated for the Frankfurt floor exchange (FWB) and for the difference between Xetra and FWB. The results are reported in table 4.4.

Table 4.4: Results Panel Regressions: The sample consists of stocks listed in Deutsche Borse's HDAX segment. The observation period comprises of 40 trading days before and after the introduction of Xetra 8 on 23 April 2007. Table 4.4 Panel A reports panel regression results for quoted spread, effective spread, and realized spread. Panel B reports regression results for price impact, permanent impact of trade innovation, and the variance decomposition in percent. The panel regression is performed on daily measures individually for each stock using the following: $LM_{i,t} = \alpha_i + \delta Xetra8_{i,t} + \beta VDAX_t + \epsilon_{i,t}$. Results are reported for the entire sample and individually by a stock's market capitalization. Stocks are divided into four groups depending on their market capitalization. Market capitalization is calculated as the product of shares outstanding and the average price. All results are reported in basis points except for variance decomposition which is in percent. *Xetra* denotes results for the Xetra, FWB denotes results for the Frankfurt floor, and Diff is Xetra-FWB. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level. Robust t-statistics are reported in parentheses.

Regressions on Spread Measures									
	Quoted Spread			Effective Spread			Realized Spread		
	Xetra	FWB	Diff	Xetra	FWB	Diff	Xetra	FWB	Diff
Sample									
Xetra8	1.12***	-1.16	2.28***	-1.91***	-0.50	-1.41***	5.39***	-0.37	5.76***
t-Value	*(3.12)*	*(-1.46)*	*(3.67)*	*(-7.43)*	*(-1.06)*	*(-3.37)*	*(16.54)*	*(-0.75)*	*(10.70)*
MCAP Q1									
Xetra8	1.06***	-0.04	1.11***	-0.53***	-0.04	-0.49***	2.20***	-0.38	2.56***
t-Value	*(5.07)*	*(-0.25)*	*(8.20)*	*(-3.75)*	*(-0.39)*	*(-2.84)*	*(6.50)*	*(-1.14)*	*(4.84)*
MCAP Q2									
Xetra8	0.43	-1.34	1.77***	-1.38***	-0.32	-1.04***	5.28***	0.50	4.77***
t-Value	*(0.46)*	*(-1.27)*	*(6.42)*	*(-2.78)*	*(-0.68)*	*(-2.77)*	*(10.24)*	*(0.89)*	*(6.95)*
MCAP Q3									
Xetra8	1.83***	-0.72	2.55***	-1.73***	-0.62	-1.12***	6.85***	-0.79	7.69***
t-Value	*(3.48)*	*(-1.18)*	*(5.86)*	*(-4.15)*	*(-1.3)*	*(-2.59)*	*(15.43)*	*(-1.05)*	*(9.44)*
MCAP Q4									
Xetra8	1.16	-2.56	3.72	-4.05***	-1.05	-3.01*	7.34***	-0.82	8.17***
t-Value	*(1.26)*	*(-0.88)*	*(1.54)*	*(-6.75)*	*(-0.61)*	*(-1.81)*	*(10.56)*	*(-0.53)*	*(5.28)*

4.5.1 Quoted Spread

Table 4.3 presents the results of the quoted spread for the full sample, pre- and post-Xetra 8.0 upgrade and separated in market capitalization quartiles. The results show that the quoted spread for the full sample decreases from 12.45 to 12.06 basis points (bps).

The results of the panel regression estimates in table 4.4 show that the Xetra upgrade had a significant negative effect on quoted spreads; when comparing with the FWB, the results on quoted spread are even greater. The results across market capitalization quartiles are varied and generally show an increase in the quoted spread. The results for the difference are more consistent and larger than for Xetra alone. Only MCap quartile 4 is not significant. Since quoted spreads only measure the trading costs for the smallest of trade sizes, a more accurate measure of execution costs is studied in the section below.

4.5.2 Effective Spread

The effective spread is the actual spread paid by a liquidity demander in a limit market. Table 4.3 reports effective spread for the full sample and individual market capitalizations both pre- and post-Xetra 8.0. In contrast to previous studies and the theoretical literature, the findings show that effective spreads decrease from an average of 8.15 bps to an average of 6.71 bps, representing a 17% decline in effective execution costs. The decrease in effective spreads can be found across market capitalization quartiles. The greatest decrease in effective spread is for small stocks, with a decrease from 25.35 to 19.04 bps.

Table 4.4 shows a significant decrease -1.91 in effective spread after the release of the new Xetra system. The results hold when compared with the FWB results (-1.41 bps). In no case is the decrease for the FWB significant and only in the smallest MCap are the results not significant for the differenced values at the 5% level. These results show clearly that post-upgrade transaction costs declined. Effective spreads are the most accurate measure of execution costs but are made up of at least two components, *viz.* the realized spread and the price impact. The interplay of these two components is important in understanding the drivers of liquidity change.

4.5.3 Realized Spread

The realized spread represents the part of the effective spread that a liquidity supplier keeps for herself. Essentially, the realized spread is a liquidity supplier's revenue and it is important to measure it in this context. A reduction in the effective spread may mean that a trade is less information-driven and hence the adverse selection costs imposed on a liquidity supplier are reduced. It could also mean that liquidity suppliers require lower compensation for the services they provide. For instance, due to decreased fixed transaction costs. Surprisingly, Table 4.3 shows that the realized spread increases by roughly three basis points. The realized spread increases across all market capitalization quartiles.

The results also hold in the panel estimation with an increase in realized spread of 5.39 bps after controlling for stock level variables and volatility. The increase is consistent across MCap quartiles and when using the differenced variables. The realized spread also increases consistently across MCap quartile. These results are surprising in that it implies that execution costs should rise after the introduction of Xetra 8 when, in fact, they decline. This result is, however, consistent with the commonly-held belief that increased execution speed leads to increased execution cost. A potential mechanism for this effect might be that liquidity suppliers require higher compensation for supplying liquidity if the chances of being exploited are greater (free-trading option) – which might be the case when execution speed increases and *arbitrageurs* are employing algorithmic trading technologies. Regardless of the explanation, it seems that the driver of the reduced execution costs is the interdependency between liquidity supplier compensation and the information content (price impact) of trades that changed after the introduction of Xetra 8.0.

4.5.4 Price Impact

Table 4.3 shows that the price impact of trades decreased significantly following the release of Xetra 8. On average, the price impact per trade decreases by four bps. The breakdown of price impact into market capitalization quartiles also shows a decrease in the price impact per trade and an increase in the magnitude of the decrease. The results remain the same in a panel regression; the price impact for the smallest stocks decreases by 11.39 basis points. The panel results show that price impact is greatly affected by the upgrade, with an overall decrease of 7.29 bps and surprisingly a 2.72 bps decrease in market capitalization Q1 stocks. The FWB and differenced results show clearly that the information content of trade on the FWB did not change and hence is not driven by any time trends. In fact, the Xetra-FWB results show a significant decrease of 7.17 bps.

4.5.5 Liquidity and Trade Size

The liquidity increase could in fact be driven by an increase in smaller trades or in liquidity for certain trades sizes. The results of the liquidity estimation regression are reported in Table 4.5.

Table 4.5: Results by Trade Size: The sample consists of stocks listed in Deutsche Borse's HDAX segment. The observation period comprises of 40 trading days before and after the introduction of Xetra 8 on 23 April 2007. Table 4.5 Panel A reports panel regression results for effective spreads by trade size. Panel B reports results for realized spreads by trade size. The regression is estimated on daily measures individually for each stock using the following: $LM_{i,t} = \alpha_i + \delta Xetra8_{i,t} + \beta VDAX_t + \epsilon_{i,t}$. Results are reported for the entire sample and individually by a stock's market capitalization. Different trade sizes are below 25,000 EUR, between 25,000 EUR and 100,000 EUR, and above 100,000 EUR. Stocks are divided into four groups depending on their market capitalization. Market capitalization is calculated as the product of shares outstanding and the average price. $Xetra$ denotes results for Xetra, FWB are results for the Frankfurt floor, and Diff is $Xetra - FWB$. All results are reported in basis points. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level. Robust t-statistics are reported in parentheses.

Panel A: Regressions on Effective Spreads by Trade Size									
	< 25 kEUR			≥ 25 kEUR and ≤ 100 kEUR			> 100 kEUR		
	Xetra	FWB	Diff	Xetra	FWB	Diff	Xetra	FWB	Diff
Sample									
Xetra8	-1.58***	-0.54	-1.04**	-3.84***	-0.79	-2.75***	-7.19***	.	.
t-Value	*(-6.35)*	*(-1.12)*	*(-2.47)*	*(-3.97)*	*(-0.89)*	*(-5.01)*	*(-4.78)*		
MCAP Q1									
Xetra8	-0.33**	-0.05	-0.28*	-0.60***	0.02	-0.57**	-1.48***	-0.45	-0.86***
t-Value	*(-2.30)*	*(-0.46)*	*(-1.65)*	*(-4.85)*	*(0.04)*	*(-2.30)*	*(-3.95)*	*(-1.01)*	*(-2.78)*
MCAP Q2									
Xetra8	-1.08**	-0.40	-0.63	-2.21***	-0.56	-1.38**	-5.17***	.	.
t-Value	*(-2.21)*	*(-0.85)*	*(-1.64)*	*(-3.22)*	*(-0.70)*	*(-2.29)*	*(-5.06)*		
MCAP Q3									
Xetra8	-1.36***	-0.71	-0.67	-3.38***	-1.20	-2.78***	-10.86***	.	.
t-Value	*(-3.42)*	*(-1.42)*	*(-1.47)*	*(-5.86)*	*(-0.97)*	*(-2.70)*	*(-4.47)*		
MCAP Q4									
Xetra8	-3.61***	-1.00	-2.61	-9.48***	-2.03	-8.42***	-16.82***	.	.
t-Value	*(-6.05)*	*(-0.58)*	*(-1.58)*	*(-4.12)*	*(-1.05)*	*(-3.54)*	*(-4.63)*		

continued below ...

... continued from Table 4.5

Panel B: Regressions on Realized Spreads by Trade Size									
	< 25 kEUR			≥ 25 kEUR and ≤ 100 kEUR			> 100 kEUR		
	Xetra	FWB	Diff	Xetra	FWB	Diff	Xetra	FWB	Diff
Sample									
Xetra8	4.89***	-0.48	5.38***	8.51***	0.39	6.89***	9.66***	.	.
t-Value	*(15.90)*	*(-0.96)*	*(9.87)*	*(11.49)*	*(0.30)*	*(5.77)*	*(7.93)*		
MCAP Q1									
Xetra8	2.05***	-0.31	2.33***	2.51***	-1.413**	3.62***	3.69***	2.00	0.87
t-Value	*(7.01)*	*(-1.01)*	*(5.16)*	*(4.48)*	*(-2.28)*	*(5.08)*	*(5.61)*	*(1.05)*	*(0.49)*
MCAP Q2									
Xetra8	4.74***	0.22	4.51***	6.97***	1.16	5.46***	11.32***	.	.
t-Value	*(9.55)*	*(0.55)*	*(7.37)*	*(6.96)*	*(0.60)*	*(2.69)*	*(8.51)*		
MCAP Q3									
Xetra8	6.21***	-0.76	7.00***	10.60***	0.20	10.85***	11.69***	.	.
t-Value	*(14.29)*	*(-0.96)*	*(8.01)*	*(11.63)*	*(0.08)*	*(4.93)*	*(5.73)*		
MCAP Q4									
Xetra8	6.69***	-1.09	7.78***	14.38***	2.62	9.77**	15.44***	.	.
t-Value	*(9.64)*	*(-0.71)*	*(4.98)*	*(6.77)*	*(0.71)*	*(2.21)*	*(3.39)*		

The largest liquidity increase is in large, small-cap trades. A dramatic fall of 16.82 bps for trades greater than 100,000 euros is found. The results are consistent with the previous analysis and confirm that liquidity increases across trade and MCap categories. For MCap groups Q2 to Q4, the Xetra-FWB estimations are not reported due to data limitations (insufficient transactions).

To ensure that the results are not in fact driven by a shift in trade size, a panel regression is performed on the average trade size. Per-trade turnover is reported in euros in Table 4.6.

Table 4.6: Results Per Trade Turnover Xetra: The sample consists of stocks listed in Deutsche Boerse's HDAX segment. The observation period comprises of 40 trading days before and after the introduction of Xetra 8 on 23 April 2007. Table 4.6 Panel A reports descripitive statistics for per trade turnover based on tick data. The mean and standard deviation are reported and calculated on each individual trade. Panel B reports panel regression results for daily per trade turnover. The panel regression is performed on daily measures individually for each stock using the following regression formula: $LM_{i,t} = \alpha_i + \delta Xetra8_{i,t} + \beta VDAX_t + \epsilon_{i,t}$. Results are reported for the entire sample and individually by a stock's market capitalization. Stocks are divided into four groups depending on their market capitalization. Market capitalization is calculated as the product of shares outstanding and the average price over the observation period for a single stock. All results are reported in Euros. The tables include results for Xetra only. All measures for the panel regressions are calculated as relative measures. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level. Robust t-statistics are reported in parentheses.

Panel A: Average Per Trade Turnover - Descriptives

	Sample		MCAP Q1		MCAP Q2		MCAP Q3		MCAP Q4	
	mean	Std. Dev.	mean	Std. Dev.	mean	Std. Dev.	mean	Std. Dev.	mean	Std. Dev.
full	49,205	96,676	63,568	113,681	30,830	57,146	17,746	26,456	11,953	19,700
pre	48,021	95,423	62,540	113,425	29,890	51,362	17,167	25,078	11,817	20,122
post	50,441	97,951	64,622	113,932	31,809	62,575	18,370	27,853	12,120	19,170

Panel B: Average Per Trade Turnover - Panel Regressions

	Sample	MCAP Q1	MCAP Q2	MCAP Q3	MCAP Q4
Xetra8	742.29	1065.37	1857.478***	85.64	-52.24
t-Value	*(1.38)*	*(0.56)*	*(2.78)*	*(0.22)*	*(-0.21)*

No statistically significant changes are found in average per-trade turnover. In Q2, a small increase is found. In all other quartiles there are statistically significant changes to turnover per trade. Their is no change in the volume ratio between Xetra and FWB. It can be safely stated that the results are robust to changes in per-trade turnover and relative volumes.

4.6 Information

To further study and confirm the hypothesis that less trade-correlated information is present post-upgrade, the analysis laid out in Hasbrouck (1991a) and Hasbrouck (1991b) is performed. The results of the VAR analysis are the average cumulative impulse response function (CIRF) over 10 events and aggregate values per stock and day.

Robust measures of trade correlated information are calculated. The permanent price impact of a trade is presented in (Hasbrouck (1991a)) and is commonly used in price discovery research. The standard settings are used, which include a forecast horizon of 10 events. Forecast validity above 10 events found no support for effects at lower frequencies. Let x_{t-i} be the trade direction. Furthermore, if r_{t-i} denotes the quote midpoint changes, then the model is as follows:

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

The estimation is restarted for each trading day and stock in the sample. The above VAR is inverted to get the vector moving average representation (VMA).

$$\begin{pmatrix} r_t \\ x_t \end{pmatrix} = \begin{pmatrix} a(L)\ b(L) \\ d(L)\ e(L)\ ) \end{pmatrix} \begin{pmatrix} u^r \\ u^x \end{pmatrix},$$

Following Hasbrouck (1991b)), the sum of $\sum_{t=0}^{10} b(L)$, where L are polynomial lag operators, is used to attain the cumulative impulse response function (CIRF). The CIRF is the permanent price impact of a trade and is generally interpreted as the private information content of a trade. Trades may contain information at lower frequencies than measured. This measure, however, has been used in a number of other studies with the same interpretation (Barclay and Hendershott (2003) Madhavan (2000)).

Using the VMA representation from above, information can be decomposed into trade-correlated and -uncorrelated portions (Hasbrouck (1991b)). The variance decomposition is as follows:

$$\sigma_w^2 = \left(\sum_{i=0}^{10} a_i\right)^2 \sigma_{u^r}^2 + \left(\sum_{i=0}^{10} b_i\right)^2 \sigma_{u^x}^2 \tag{4.2}$$

The information content of quotes is the first term and the trade correlated portion is the second term. All lags are summed to get the total contribution to price discovery of both portions. These results are reported below in basis points for the CIRF and in percent for the information content of quotes in relation to all information impounded into the market. By analyzing both of these measures, the mechanism by which information is impounded into prices is studied. Lacking sharp theoretical predictions, the statistical null hypothesis is simply that there will be no difference between the trade-correlated and -uncorrelated information, post upgrade. To test for differences in the amount of trade-correlated and -uncorrelated information pre- and post-upgrade, the same regression as above is estimated for the price impact (for Xetra), CIRF and the variance decomposition. The results of the estimation are presented in Table 4.7.

Table 4.7: Results Panel Regressions: The sample consists of stocks listed in Deutsche Börse's HDAX segment. The observation period comprises of 40 trading days before and after the introduction of Xetra 8 on 23 April 2007. Table 4.4 Panel A reports panel regression results for quoted spread, effective spread, and realized spread. Panel B reports regression results for price impact, permanent impact of trade innovation, and quote-based price discovery in percent. The panel regression is performed on daily measures individually for each stock using the following: $LM_{i,t} = \alpha_i + \delta Xetra8_{i,t} + \beta VDAX_t + \epsilon_{i,t}$. Results are reported for the entire sample and individually by stock market capitalization. Market capitalization is calculated as the product of shares outstanding and the average price over the observation period for a single stock. All results are reported in basis points expect for quote impounded information which is measured in percent. Xetra denotes results for the Xetra System, FWB denotes results for the Frankfurt floor, and Diff denotes Xetra-FWB. All measures for the panel regressions are calculated as relative measures. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level. Robust t-statistics are reported in parentheses below panel regressions' coefficients.

Panel B: Adverse Selection and Quote Fraction					
	Price Impact			Trade Innovation	Var. Decomp.
	Xetra	FWB	Diff	Xetra	Xetra
Sample					
Xetra8	-7.29***	-0.13	-7.17***	-3.16***	47.89***
t-Value	*(-17.32)*	*(-0.42)*	*(-14.44)*	*(-21.04)*	*(72.04)*
MCAP Q1					
Xetra8	-2.72***	0.34	-3.04***	-1.60***	47.74***
t-Value	*(-6.96)*	*(1.01)*	*(-4.91)*	*(-16.05)*	*(34.80)*
MCAP Q2					
Xetra8	-6.66***	-0.82	-5.81***	-2.89***	50.87***
t-Value	*(-9.80)*	*(-1.13)*	*(-7.09)*	*(-13.39)*	*(41.08)*
MCAP Q3					
Xetra8	-8.58***	0.17	-8.81***	-3.54***	48.80***
t-Value	*(-18.93)*	*(0.29)*	*(-13.85)*	*(-22.33)*	*(35.11)*
MCAP Q4					
Xetra8	-11.39***	-0.22	-11.18***	-4.70***	44.17***
t-Value	*(-17.22)*	*(-0.36)*	*(-12.43)*	*(-16.48)*	*(48.68)*

Table 4.7 reports a strongly negative effect of the Xetra upgrade on the CIRF. The Xetra results are highly significant (-21.04) with a coefficient of -3.16 (table 4.7). These results confirm the results of the price impact analysis. Unfortunately, due to data restrictions, the CIRF cannot be calculated for the FWB. The price impact

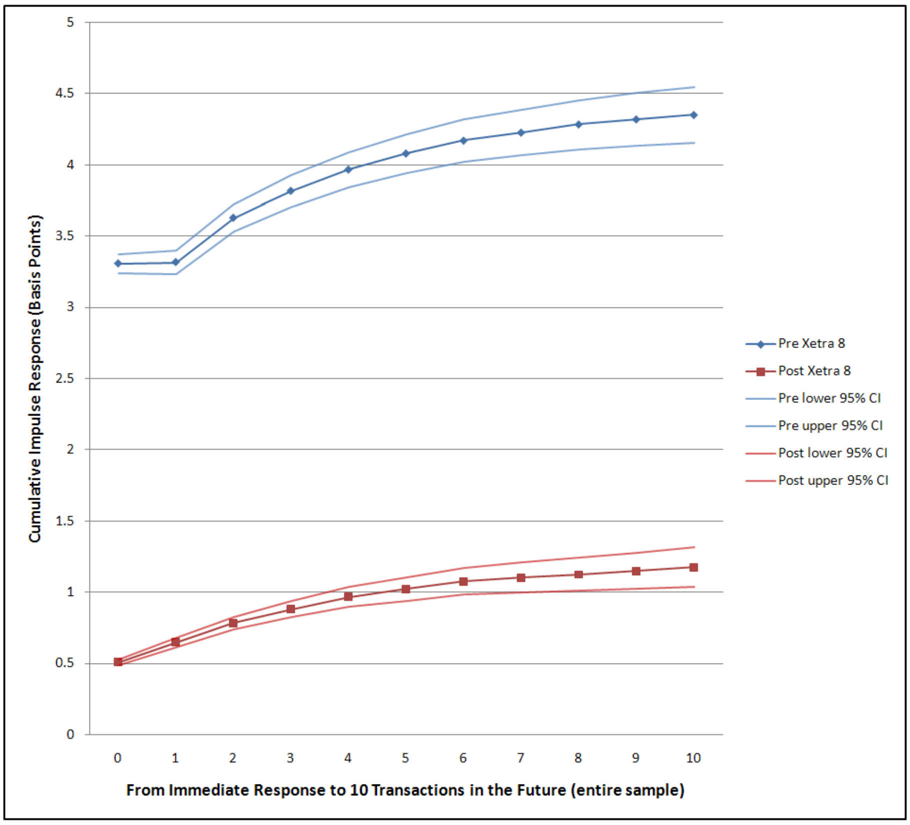

Figure 4.3: Cumulative Impulse Response (Basis Points) - Entire Sample: In this figure the cumulative impulse response of a trade is on the y-axis. The x-axis is the forecast horizon in trades. The blue lines are pre-event with 95% confidence intervals. The red values are post-events with 95% confidence intervals.

remains unchanged for the FWB pre- and post-upgrade. The effect of the Xetra upgrade on the CIRF increases in absolute terms across MCap quartiles, indicating that liquidity suppliers are able to avoid informed trades post-upgrade in relatively small stocks that generally have larger adverse selection costs.

Figure 4.3 presents the CIRF pre and post-upgrade for the entire sample. Ninety-five percent confidence intervals are included and clearly show post-upgrade trade related information is strictly and always smaller than that measured in the pre-upgrade period.

The forecast horizon in trades is reported on the X-axis (0 - 10). At 10 trades the trade impact levels off, confirming the lag length selected. On the Y-axis the CIRF is graphed in basis points. Similar graphics are included for each of the 4 MCap quartiles. These are presented in the Appendix 4.9 in figures 4.5, 4.6, 4.7, and 4.8

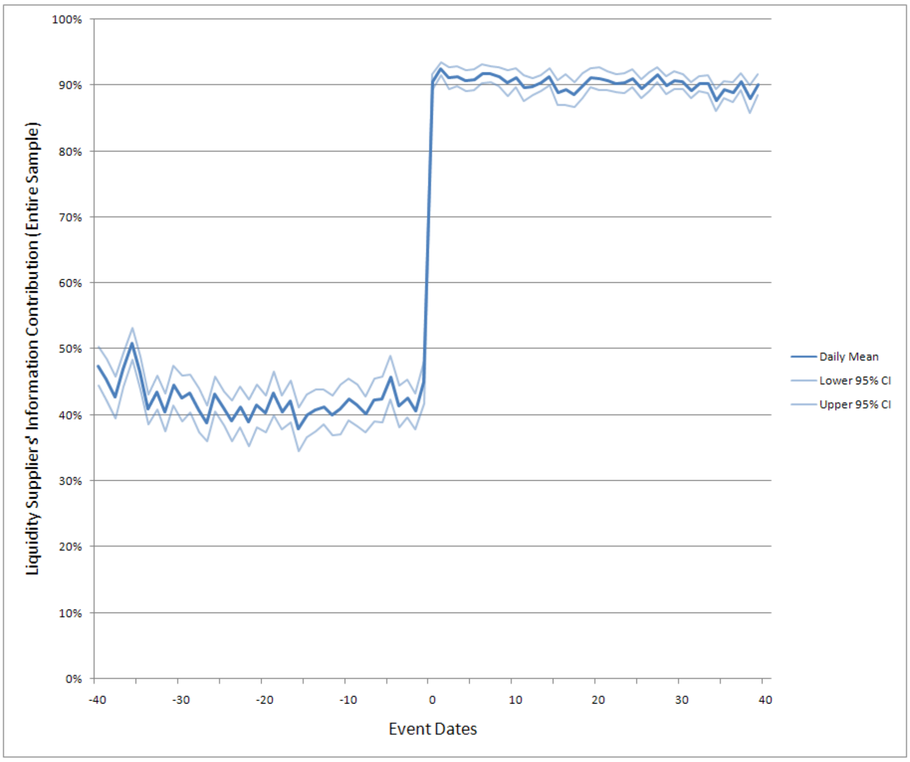

Figure 4.4: Quoted Based Information (Percent) - Entire Sample: The figure graphs the non-trade/quote-based correlated information with 95% confidence intervals. The events dates are on the x-axis and the quote-based contribution in percent is on the y-axis.

and they confirm the results presented above and show an increase in the difference across quartiles.

Table 4.7 reports a dramatic increase in the amount of information being impounded into prices via quotes. Quote-based information increases by 47.89% and is highly significant at the 1% level. In figure 4.4, the percentage of quote-based information across the sample period with 95% confidence intervals is graphed, similar to the above figures.

Visual inspection clearly shows that the ratio changes dramatically on the event day. The statistical test in table 4.7 simply confirms what visual inspection already reveals. As above, similar figures are included for each MCap group in Appendix 4.9 figures 4.9, 4.10, 4.11, and 4.12.

A test of the equality of variance is included to better understand the information impounding process. In Panel A of table 4.8, the mean and standard deviation of the quote-based information pre and post-upgrade is reported. The standard deviation falls by roughly half. An equality of means test is estimated and the results are reported in Panel B.

Table 4.8: Equality of Variances of Quote Based Information: The sample consists of stocks listed in Deutsche Börse's HDAX segment. The observation period comprises of 40 trading days before and after the introduction of Xetra 8 on 23 April 2007. Table 4.8 Panel A reports descriptive statistics for mean and standard deviation of the variance decomposition before and after the introduction of Xetra 8. Panel B reports results of the Brown and Forsythe (1974) robust test for the equality of variances for the quote based information fraction before and after the introduction of Xetra 8. The tests and descriptives are based on daily per instrument data. The test is a modified Levene test and more robust against non-normality than the normal Levene test.

Panel A: Quote Based Information Fraction - Descriptives

	Sample		MCAP Q1		MCAP Q2		MCAP Q3		MCAP Q4	
	mean	Std. Dev.	mean	Std. Dev.	mean	Std. Dev.	mean	Std. Dev.	mean	Std. Dev.
pre	42%	15%	42%	12%	39%	14%	43%	15%	45%	19%
post	90%	8%	90%	6%	90%	8%	92%	7%	90%	10%

Panel B: Quote Based Information - Equality of Variances Before and After Event

	Sample	MCAP Q1	MCAP Q2	MCAP Q3	MCAP Q4
F-value	1,272.91	291.23	271.22	421.83	361.64
p-value	<.0001	<.0001	<.0001	<.0001	<.0001

Using the modified Levene Test, the null hypothesis of equal variances pre- and post-upgrade is rejected. This is interpreted as confirmatory evidence that AT may be driving this trend. Imagine a situation where humans are doing most of the public information (trades, quotes, orders) processing. The level of attention of a human is variable throughout a day and is also bounded. On days where there is a high level of activity, the proportion of information processed will be lower than on days with less information. Limited attention and variability are not attributes one would typically associate with an algorithm. AT are more likely to provide non-variable levels of information processing which are considerably less dependent on the amount of information or time of day.

4.6.1 Information and Trade Size

Technical innovations have been shown to impact the amount and nature of trade in electronic stock markets (Campbell, Lo, and MacKinlay (1997) and Stoll (2006)). The raises the question: Is the effect driven by trade-size? To analyze the effect of trade size, the sample is broken into three-trade size categories: smaller than $25,000$; between $25,000$ and $100,000$; and greater than $100,000$ euros. Table 4.9 reports the results of a regression of the price impact per trade on the Xetra 8 variable. The trend towards an increase in the absolute decrease of the price impact remains across MCaps and trade size. Due to data restrictions, it was impossible to calculate values for the difference between Xetra and the FWB for large trades.

Table 4.9: Results Panel Regressions by Trade Size: The sample consists of stocks listed in Deutsche Börse's HDAX segment. The observation period comprises of 40 trading days before and after the introduction of Xetra 8 on 23 April 2007. Filters applied to HDAX stocks reduce the sample to 101 continuously trades stocks. Table 4.9 reports panel regression results for price impacts by trade size. The panel regression is performed on daily measures individually for each stock using the follwing regression formula: $LM_{i,t} = \alpha_i + \delta Xetra8_{i,t} + \beta VDAX_t + \epsilon_{i,t}$. The regression tests the null-hypothesis of no influence of the Xetra 8 update on liquidity and information measures. Results are reported for the entire sample and individually by a stock's market capitalization. Different trade sizes are below 25,000 EUR, between 25,000 EUR and 100,000 EUR, and above 100,000 EUR. Stocks are divided into four groups depending on their market capitalization. Market capitalization is calculated as the product of shares outstanding and the average price over the observation period for a single stock. Xetra denotes results for the Xetra System, FWB denotes results for the Frankfurt floor, and Diff denotes Xetra-FWB. All results are reported in basis points. All measures for the panel regressions are calculated as relative measures. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level. Robust t-statistics are reported in parantheses below panel regressions' coefficients.

Regressions on Price Impacts by Trade Size									
	< 25 kEUR			≥ 25 kEUR and ≤ 100 kEUR			> 100 kEUR		
	Xetra	FWB	Diff	Xetra	FWB	Diff	Xetra	FWB	Diff
Sample									
Xetra8	-6.48***	-0.05	-6.42***	-12.35***	-1.18	-9.64***	-16.85***	.	.
t-Value	*(-16.38)*	*(-0.18)*	*(-12.84)*	*(-11.45)*	*(-0.96)*	*(-8.38)*	*(-8.80)*		
MCAP Q1									
Xetra8	-2.38***	0.26	-2.61***	-3.11***	1.44*	-4.20***	-5.16***	-2.44	-1.73
t-Value	*(-6.85)*	*(0.87)*	*(-4.86)*	*(-4.95)*	*(1.72)*	*(-5.74)*	*(-5.80)*	*(-1.34)*	*(-0.94)*
MCAP Q2									
Xetra8	-5.82***	-0.63	-5.15***	-9.18***	-1.72	-6.84***	-16.48***	.	.
t-Value	*(-8.85)*	*(-1.00)*	*(-6.40)*	*(-8.40)*	*(-0.88)*	*(-3.31)*	*(-9.27)*		
MCAP Q3									
Xetra8	-7.58***	0.06	-7.67***	-13.98***	-1.40	-13.63***	-22.55***	.	.
t-Value	*(-16.79)*	*(0.10)*	*(-11.19)*	*(-13.13)*	*(-0.62)*	*(-7.25)*	*(-8.90)*		
MCAP Q4									
Xetra8	-10.30***	0.08	-10.40***	-23.86***	-4.65	-18.19***	-32.25***	.	.
t-Value	*(-15.58)*	*(0.13)*	*(-10.59)*	*(-9.81)*	*(-1.56)*	*(-5.13)*	*(-6.48)*		

Although there is an increase in the trade size, the post upgrade effect is largely statistically insignificant, as seen in Table 4.6. It is interesting that as quotes become more informative (quote-based price discovery increases), participants are willing to trade in larger blocks. Perhaps there were more smaller limit orders being picked-off pre-upgrade, which would explain both the increase in trade size and the greater pre-upgrade CIRF. What is clear is that a change in trade size is not driving the results.

4.7 Discussion and Interpretation

The preceding demonstrated how information is being impounded into prices. The CIRF is generally interpreted as being private information. The non-trade-correlated information content of quotes is generally interpreted as being public information. If the hypothesis that market changes result from AT's effect of reducing latency are accepted, it is must be that AT are processing considerably more public information post upgrade. By processing more public information, AT are making quotes more informative and thereby increasing liquidity.

To make sense of the results, two AT strategies are analyzed. Why the focus on AT strategies only? The sole purpose of the Xetra 8.0 upgrade was to reduce minimum latency from 40 to 10 milliseconds (ms). Depending on the task, humans can process and use information roughly every 300 ms. The Xetra 8.0 upgrades are beyond the processing capacity of humans and can only be exploited by algorithms.

In the following interpretation, two groups of AT are introduced that may explain the changes in liquidity and the information content of trades and quotes. Most of the results can be explained using these two scenarios. The groups are similar to those found in the new NYSE program trading description, and are mirrored in Hasbrouck and Saar (2009). Both identify two distinct types of AT. They call these groups *agency* and *proprietary* AT.

Agency AT is essentially the automation of typical broker tasks. An agency AT trade would optimally slice a large order into smaller pieces and thereby reduce the cost of liquidity. There is no evidence in the data to support the conjecture that reducing latency would impact agency AT trading strategies. The AT proprietary group might represent an entirely new type of trader. Proprietary AT is, in-part, the automation of informed short-term trading. These traders typically monitor a number of markets and securities for profitable trading opportunities. This type of trading includes some forms of program trading (Stoll and Whaley (1987)), future and spot market arbitrage (Brennan and Schwartz (1990)), and correlated pairs trading. These traders may also supply liquidity algorithmically as in Hakansson, Beja, and Kale (1985).

If by reducing latency this second group of AT gained an advantage over the first group of AT, and humans in general, what effects would one expect to observe in the market? As AT increases, so does market monitoring. As the costs of monitoring decrease (lower technology frictions), quotes may also become more informative. The mechanism is quite simple; AT with information about future short-term price changes may submit a liquidity demanding trade to profit from the information, or quotes at which they expected not to be adversely exposed to the free-trading option. They would submit more quotes when liquidity costs exceed their information. The corollary is that the trade-correlated portion of trades will also fall because AT will use their information processing abilities to compete away profits. Essentially when liquidity is demanded, it will be demanded at prices that are more informationally efficient. These trades will by definition have a lower permanent impact on the efficient security price.

This finding is reflected in the realized spreads results. Although the information content of trades falls dramatically, the effective spread only falls minimally. The surplus is skimmed by liquidity suppliers in the market. These liquidity suppliers are in less competition with one another than before, and are able to keep the largest portion of the surplus.

4.8 Conclusion

In this paper, the effect of reducing latency on market-wide information and liquidity is studied. Common measures of information in a market microstructure sense and measures of the actual transaction costs paid by market participants are used. The results show that quote-based information increases in concert with liquidity. The Xetra 8.0 upgrade is ideal to test the hypotheses that latency reductions affect information and liquidity. It is shown that reducing latency does cause an increase in liquidity. This is in contrast to the results found in Hendershott and Moulton (2007) and theorized much early by Demsetz (1968).

The increase in liquidity is due to a dramatic drop in the information content of trades and a somewhat less dramatic increase in realized spread. Two algorithmic trading scenarios are presented that may be driving these results. The reduction in latency seems to be a win-win situation for regulators, market participants and exchange operators. Most importantly to regulators, prices are more efficient post upgrade by better reflecting public information in the quotes before trades take place. As adverse selection costs fall, market participants are also more likely to trade. Also of importance to market participants is the fact that they can execute their orders at a lower cost. Exchange operators are content because they attract higher volumes and corresponding fees. One would imagine that, as the level of competition between algorithmic liquidity suppliers reaches that of humans prior to the Xetra 8.0 upgrade, liquidity will continue to increase. A warning is, however, in order. Even simple systems changes may have unexpected effects on markets. The mechanism, better quotes, by which liquidity improved was little understood before the upgrade and likely not the expected one. The effect of reducing latency could have been to reduce liquidity as in NYSE's Hybrid upgrade.

Future work in the area should focus on the theoretical underpinning of these results. Why is it that the NYSE Hybrid upgrade caused a decrease in liquidity while a similar execution speed increase at the DB had the opposite effect? Also further studies into similar recent upgrades (TSX Quantum, LSE Tradelect, Euronext Universal Trading Platform) could shed light on some of these differences. Finally more detailed algorithmic trading data sets, presented in the following chapter, could also help to alleviate some of the suspicions with regards to algorithmic trading.

4.9 Appendix - Chapter 4

Table 4.10: Summary Sample Statistics: The sample consists of stocks listed in Deutsche Börse's HDAX segment. The observation period comprises of 40 trading days before and after the introduction of Xetra 8 on 23 April 2007. Filters applied to HDAX stocks reduce the sample to 101 continuously trades stocks. This table reports stock symbol, average, minimum, maximum and the standard deviation of the price.

	Price			
Stock	Av.	Min.	Max.	Std. Dev.
ADAG	7.70	6.44	9.50	0.61
ADSG	42.13	34.50	47.49	3.59
AIXG	5.69	4.15	7.11	0.63
ALTG	35.88	17.53	55.89	14.76
ALVG	161.63	145.50	176.29	6.02
AMBG	115.44	112.25	119.73	1.69
ARLG	37.28	32.50	40.25	1.62
ATSV	18.61	16.14	20.44	0.95
AWDG	34.82	30.54	38.20	1.54
BASF	85.02	74.42	95.15	5.47
BAYG	49.24	41.07	57.55	4.10
BC8G	23.16	18.50	27.77	1.66
BEIG	51.98	47.02	55.30	1.94
BIOZ	57.91	53.72	61.00	1.89
BMWG	45.77	40.44	51.49	2.93
BOSG_p	43.61	37.00	49.69	2.47
CBKG	34.34	29.67	38.20	2.36
CGYG	54.83	47.34	61.13	3.09
CLSGn	48.45	41.13	55.00	2.86
CONG	100.07	89.60	108.65	4.79
DBKGn	106.45	90.61	118.51	7.45
DCXGn	60.69	49.55	69.62	5.28
DEQGn	57.85	54.01	61.37	1.27
DEZG	10.68	9.42	12.09	0.57
DOHG	46.15	42.25	50.45	2.10
DPBGn	65.34	58.54	74.71	2.91
DPWGn	23.75	21.77	26.30	0.96
DRWG_p	67.03	57.20	74.68	4.15
DTEGn	13.13	12.19	14.56	0.55
EAD	23.39	21.50	26.25	1.03
EONG	108.27	94.50	125.06	7.84
EPCGn	14.55	11.54	16.98	1.52
ES6G	56.48	46.78	60.60	2.65

continued below ...

... continued from Table 4.10

	Price			
Stock	Av.	Min.	Max.	Std. Dev.
EVTG	3.63	3.16	4.39	0.23
FRAG	55.30	50.62	64.96	2.81
G1AG	20.39	15.70	24.40	2.27
GBFG	67.94	57.61	74.72	4.13
GFJG	19.88	17.33	23.41	1.18
GPCG	21.18	18.70	25.16	1.19
HDDG	35.36	30.59	40.51	1.92
HEIG	114.29	105.14	121.29	3.88
HNRGn	34.54	30.01	37.79	1.85
HOTG	76.40	59.70	91.50	7.69
HRXG	49.01	44.40	53.65	1.89
IDRG	16.22	14.50	18.59	1.25
IFXGn	11.47	10.78	12.37	0.29
IKBG	28.90	25.65	32.67	1.36
IVGG	33.12	28.35	37.42	2.01
IWKG	23.87	20.65	26.20	1.22
JENG	7.63	6.70	8.22	0.31
KARG	27.23	24.10	29.52	1.15
KBCG	12.91	10.22	14.79	1.13
KCOGn	46.11	34.55	56.77	5.44
KRNG	148.40	115.00	173.47	14.52
LEOGn	32.50	29.05	35.77	1.78
LHAG	21.04	19.56	22.70	0.80
LING	80.47	74.12	85.42	2.20
LXSG	39.42	34.89	43.75	1.95
MANG	94.69	77.10	112.40	9.55
MEOG	56.63	50.46	63.69	3.44
MLPG	18.07	15.35	19.70	0.98
MORG	52.21	45.50	59.43	2.73
MRCG	97.84	87.65	109.21	4.00
MTXGn	42.84	35.20	47.89	2.63
MUVGn	128.61	112.35	142.75	7.89
NAFG	26.08	22.25	33.25	2.59
NDXGk	25.99	18.55	31.22	2.53
P1ZGn	16.69	13.79	23.19	2.31
PFDGn	23.25	20.32	25.66	1.17
PRAG	28.97	24.02	34.50	2.54
PREGn	16.45	14.34	18.70	0.98
PSMG_p	26.76	24.26	30.35	1.15
PUMG	310.04	256.44	351.70	32.19

continued below ...

... continued from Table 4.10

	Price			
Stock	Av.	Min.	Max.	Std. Dev.
PV	69.23	57.10	77.96	5.00
QCEG	52.16	40.60	65.88	5.97
QGEN	12.68	11.60	13.72	0.44
QSCG	5.47	4.84	6.35	0.37
RHKG	43.67	38.05	48.17	2.26
RHMG	68.39	57.26	76.88	4.61
RWEG	79.60	74.14	85.50	2.46
SAPG	35.32	32.83	38.31	1.06
SDFG	91.80	74.72	111.96	9.29
SGCG	25.40	17.25	33.72	3.70
SIEGn	89.10	75.87	107.18	7.84
SNGG	11.09	9.96	13.40	0.66
SOOG	40.33	35.00	44.30	1.57
SOWG	64.52	52.51	73.75	4.40
SRZG	107.11	101.50	112.95	1.53
STAGn	46.46	39.25	51.20	2.03
SWVG	60.07	49.75	68.70	3.54
SZGG	121.27	88.13	152.18	17.58
SZUG	15.35	13.29	16.71	0.79
TATL	16.20	14.78	17.89	0.61
TKAG	39.99	35.00	46.53	3.13
TNHG	55.21	52.01	58.02	1.29
TUIGn	19.32	16.80	22.10	1.37
UTDI	14.01	12.12	15.82	0.54
VOSG	75.54	58.65	94.47	6.98
VOWG	107.14	90.01	119.18	7.19
WCHG	138.41	108.45	176.00	15.46
WDIG	9.06	6.90	10.50	0.94

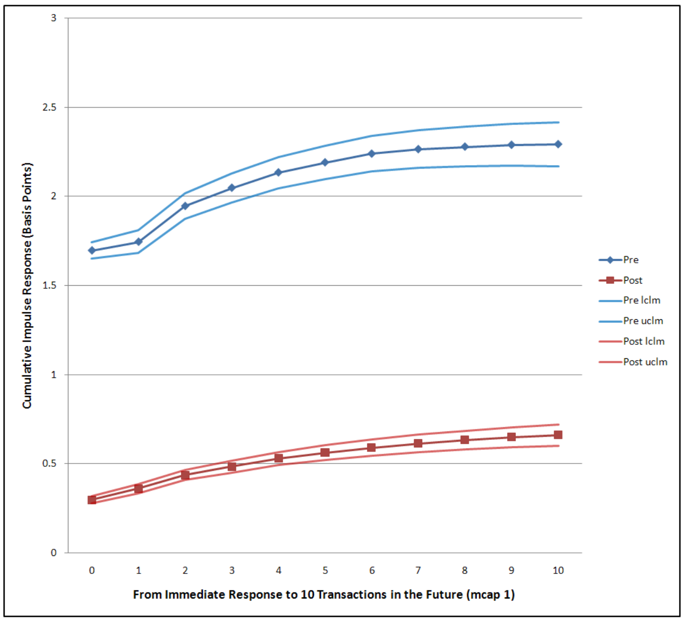

Figure 4.5: Cumulative Impulse Response - MCap 1: In this figure the cumulative impulse response of an event is on the y-axis. The x-axis is the forecast horizon in events. The blue lines are pre-event with 95% confidence intervals and the red values are post-event.

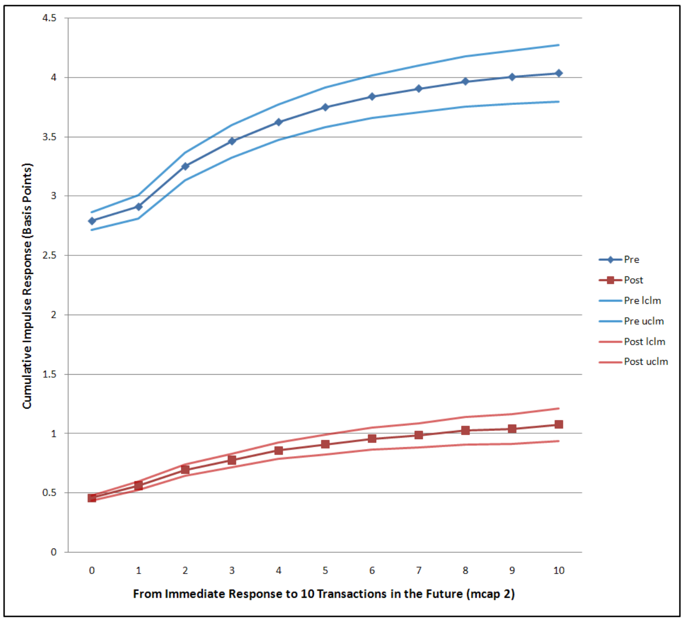

Figure 4.6: Cumulative Impulse Response - MCap 2: In this figure the cumulative impulse response of an event is on the y-axis. The x-axis is the forecast horizon in events. The blue lines are pre-event with 95% confidence intervals and the red values are post-event.

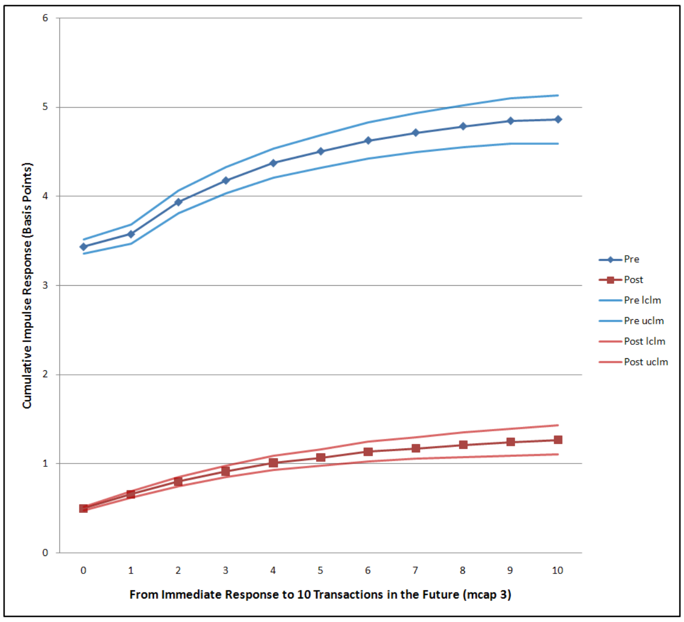

Figure 4.7: Cumulative Impulse Response - MCap 3: In this figure the cumulative impulse response of an event is on the y-axis. The x-axis is the forecast horizon in events. The blue lines are pre-event with 95% confidence intervals and the red values are post-event.

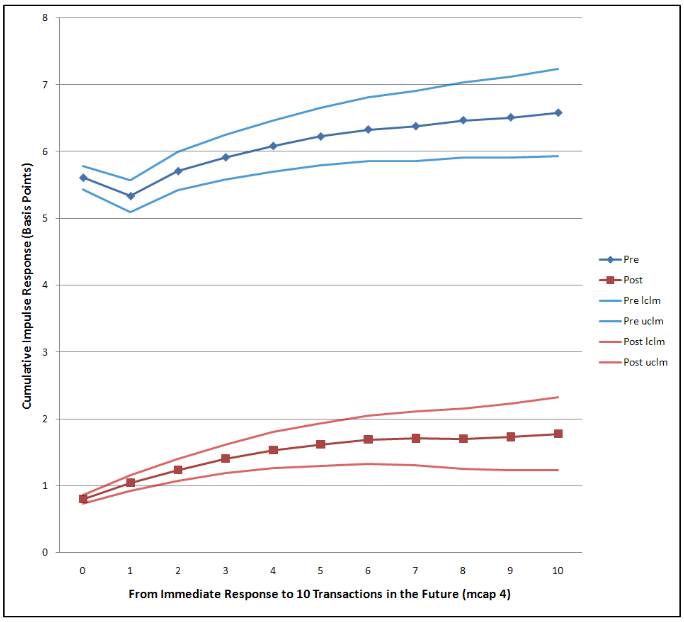

Figure 4.8: Cumulative Impulse Response - MCap 4: In this figure the cumulative impulse response of an event is on the y-axis. The x-axis is the forecast horizon in events. The blue lines are pre-event with 95% confidence intervals and the red values are post-event.

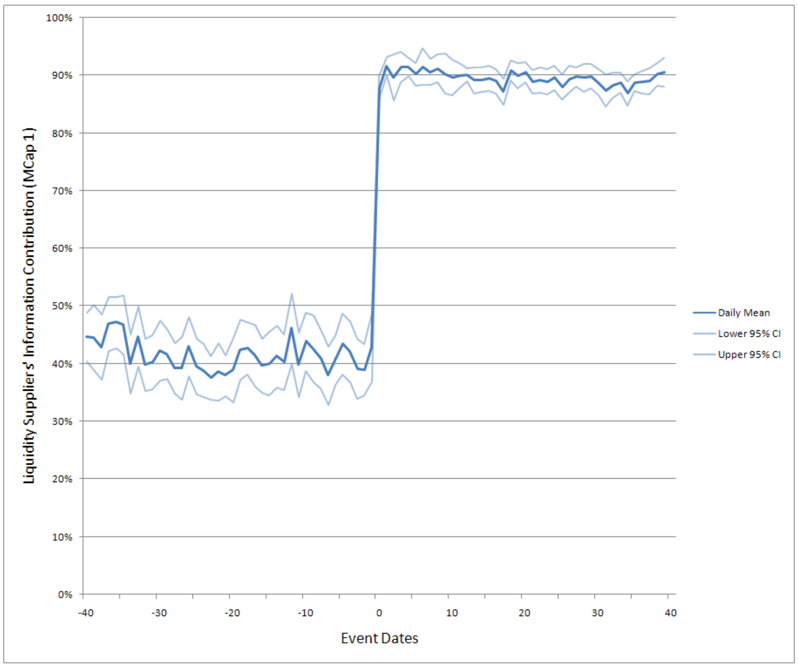

Figure 4.9: Quoted Based Information (Percent) - MCap 1: The figure graphs the non-trade/quote-based correlated information with 95% confidence intervals for MCap 1. The events dates are on the x-axis and the quote-based contribution in percent on the y-axis.

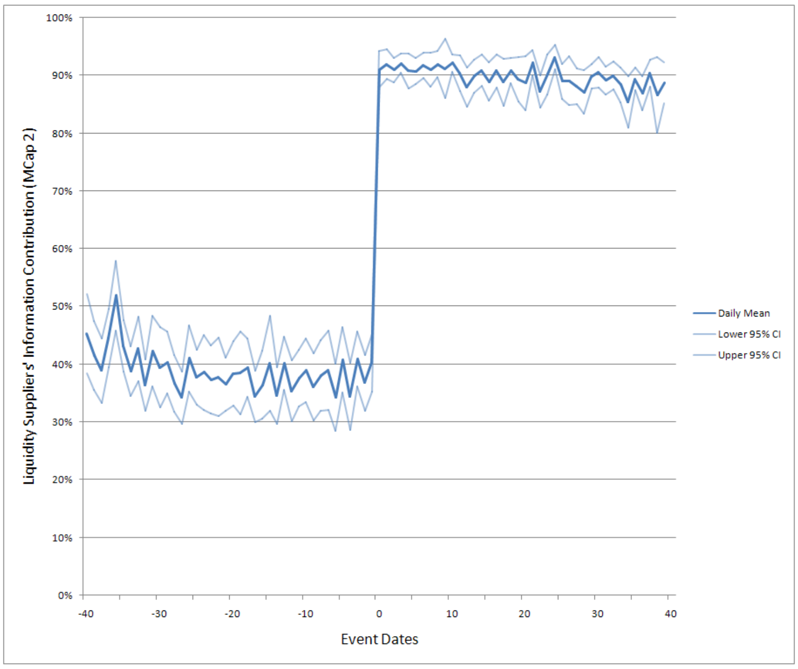

Figure 4.10: Quoted Based Information (Percent) - MCap 2: The figure graphs the non-trade/quote-based correlated information with 95% confidence intervals for MCap 2. The events dates are on the x-axis and the quote-based contribution in percent on the y-axis.

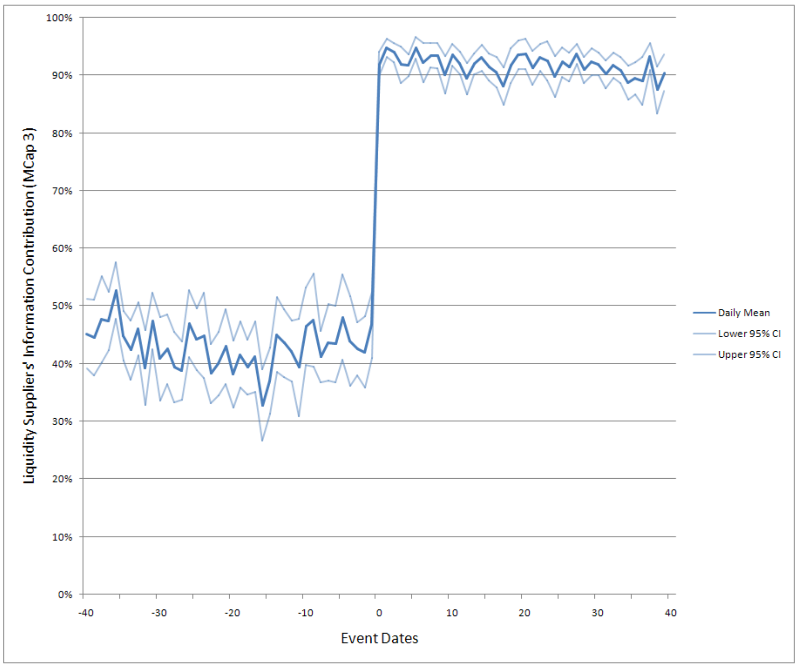

Figure 4.11: Quoted Based Information (Percent) - MCap 3: The figure graphs the non-trade/quote-based correlated information with 95% confidence intervals for MCap 3. The events dates are on the x-axis and the quote-based contribution in percent on the y-axis.

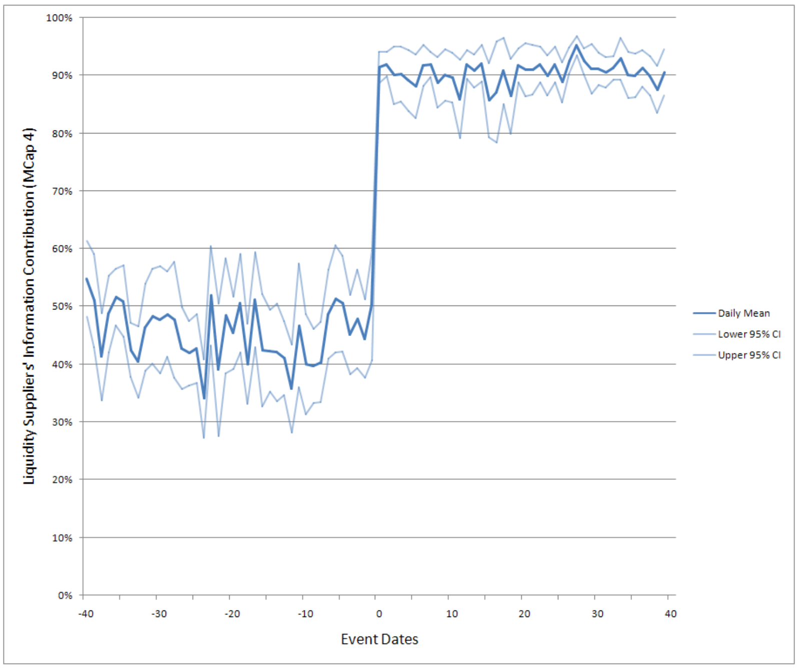

Figure 4.12: Quoted Based Information (Percent) - MCap 4: The figure graphs the non-trade/quote-based correlated information with 95% confidence intervals for MCap 4. The events dates are on the x-axis and the quote-based contribution in percent on the y-axis.

Chapter 5

Algorithmic Trading and Information

Algorithmic trades and their role in the price discovery process in the 30 DAX stocks on the Deutsche Boerse are explored. AT liquidity demand represents 52% of volume and AT supplies liquidity on 50% of volume. Algorithmic traders act strategically by monitoring the market for liquidity and deviations of price from fundamental value. Algorithmic Traders consume liquidity when it is cheap and supply liquidity when it is expensive. Algorithmic Traders contribute more to the efficient price by placing more efficient quotes and by Algorithmic Traders demanding liquidity to move the prices towards the efficient price.

5.1 Introduction

Technology has revolutionized the way financial markets function and the way financial assets are traded. Two significant interrelated technological changes are investors using computers to automate their trading processes, and markets reorganizing themselves so virtually all are now electronic limit order books (Jain (2005)). The speed and quality of access to such markets encourages the use of AT, commonly defined as the use of computer algorithms to automatically make trading decisions, submit orders, and manage those orders after submission. Because the trading process is central to efficient risk sharing and price efficiency, it is important to understand how AT is used as well as its role in the price formation process. These issues are examined for DAX stocks (the 30 largest market capitalization stocks) traded on the Deutsche Boerse (DB) with data identifying whether or not each trade's buyer and seller generated their order with an algorithm. Directly identifying AT is not possible in most markets, so relatively little is known.[1]

Liquidity demanders use algorithms to try to identify when a security's price deviates from the efficient price. They do this by quickly processing information contained in order flow and price movements in that security and in other securities across markets. Liquidity suppliers must follow a similar strategy to avoid being picked off. Institutional investors also utilize AT to trade large quantities gradually over time, thereby minimizing market impact and implementation costs.

Most markets offer volume discounts to attract high-frequency traders. The development costs of AT typically lead to it being adopted first by high-volume users who automatically qualify for the quantity discounts. The German competition authority does not allow for generic volume discounts but rather requires that such discounts have a cost sensitive component. The DB successfully asserted that algorithm generated trading is both lower cost and highly sensitive to cost reductions and, therefore, could receive quantity discounts. In December of 2007, the DB introduced its fee rebate program for automated traders. The DB provided data on AT orders in the DAX stocks for the first three weeks of January 2008.

Algorithmic traders initiate 52% of trading volume via marketable orders. They initiate smaller trades with AT initiating 68% of volume for trades of less than 500 shares and 23% of volume for trades of greater than 10,000 shares. AT initiate trades quickly when spreads are small and cluster their trades together, and are

[1] Biais and Weill (2008) theoretically examine the relation between AT, market monitoring, and liquidity dynamics. Chaboud et al. (2009) study AT in the foreign exchange market. Hendershott, Jones, and Menkveld (2008) use a proxy for AT to examine AT's effect on liquidity in the equity market.

more sensitive to human trading activity than are humans to AT activity. These are all consistent with AT closely monitoring the market for trading opportunities. If an algorithmic trader is constantly monitoring the market, the trader can break up their order into small pieces to disguise their intentions and quickly react to changes in market conditions. AT could also be trying to exploit small deviations of price from fundamentals.

In an effort to move beyond unconditional measures of AT activity, probit models of AT are estimated using the market conditions variables incorporating the state of the limit order book and past volatility and trading volume. AT are found to be more likely to initiate trades when liquidity is high in terms of narrow bid-ask spreads and higher depth. In the 15 prior minutes, AT-liquidity-demanding trades are not related to volatility but during the same time span, AT initiated trading is negatively related to volume.

Just as algorithms are used to monitor liquidity in the market, they may also be used to identify and capitalize on short-run price predictability. A standard VAR (Hasbrouck (1991a) and Hasbrouck (1991b)) is used to examine the return-order flow dynamics for both AT and human trades. AT-liquidity-demanding trades play a more significant role in discovering the efficient price than do human trades. AT-initiated trades have a more than 20% larger permanent price impact than do human trades. In terms of the total contribution to price discovery – decomposing the variance of the efficient price into its trade-correlated and non trade-correlated components – AT liquidity demanding trades help impound 40% more information than do human trades.

The conditions under which AT supply liquidity via non-marketable orders is also examined. The nature of the data makes it possible to build an AT-only limit order book, but makes it difficult to perfectly identify when AT supply liquidity in transactions (see Section 5.3 for exact details). Therefore, the focus of the analysis is on quoted prices associated with AT versus humans. While AT supply liquidity for exactly 50% of trading volume, AT are at the best price (inside quote) more often than are humans. This is AT-human difference is more pronounced when liquidity is lower, demonstrating that AT supply liquidity more when liquidity is expensive.

The role of AT quotes in the price formation process is also examined. The information shares (Hasbrouck (1995)) are calculated, for AT and human quotes. AT quotes play a much more significant role in the price formation process than their 50% of trading volume would suggest. The information shares decompose the changes in the efficient price into components that occur first in AT quotes, followed by human quotes, and then finally appear contemporaneously in AT and human quotes – the corresponding breakdown being roughly 50%, 40%, and 10%, respectively. The ability of AT to update quotes quickly based on changing market conditions may allow AT to better provide liquidity during challenging market conditions.

The results on AT liquidity supply and demand suggest that AT monitor liquidity and information in the market. AT consume liquidity when it is cheap and supply liquidity when it is expensive, smoothing out liquidity over time. AT also contribute more to the efficient price by having more efficient quotes and by AT demanding liquidity so as to move the prices towards the efficient price. Casual observers often blame the recent increase in market volatility on AT[2]. AT demanding liquidity during times when liquidity is low could result in AT exacerbating volatility, but no evidence of this is found. AT could also exacerbate volatility by not supplying liquidity as it dries up. However, the opposite is found in the current analysis.

Section 5.2 relates the work to existing literature. Section 5.4 describes the data. Section 5.5 analyzes when and how AT demand liquidity. Section 5.6 examines how AT demand liquidity relates to discovering the efficient price. Section 5.7 studies when AT supply liquidity and its relation to discovering the efficient price. Section 5.8 provides a conclusion.

[2]For example, see "Algorithmic trades produce snowball effects on volatility," *Financial Times*, December 5, 2008.

5.2 Literature Review

Due to the difficulty in identifying AT, most existing research directly addressing AT has used data from brokers who sell AT products to institutional clients. Engle, Russell, and Ferstenberg (2007) use execution data from Morgan Stanley algorithms to study the tradeoffs between algorithm aggressiveness and the mean and dispersion of execution cost. Domowitz and Yegerman (2006) study execution costs of ITG buy-side clients, comparing results from different algorithm providers.

Several recent studies use comprehensive data on AT. Chaboud et al. (2009) study the development of AT in the foreign exchange market on the electronic broking system (EBS) in three currency pairs, *viz.* euro-dollar; dollar-yen; and euro-yen. Similar to the results reported here, they find little relation between AT and volatility. In contrast to these results, Chaboud et al. (2009) find that non-algorithmic order flow accounts for most of the variance in FX returns. This surprising result may be due to either EBS' origins as an interdealer market where algorithms were closely monitored, to humans in an interdealer market being more sophisticated than humans in equity markets, or to there being relatively little private information in FX. Chaboud et al. (2009) find that AT seem to follow correlated strategies, which is consistent with the results of AT clustering together. Hendershott, Jones, and Menkveld (2008) use a proxy for AT, message traffic, which is the sum of order submissions, order cancelations, and trades. Unfortunately, such a proxy makes it difficult to closely examine when and how AT works and its precise role in the price formation process. For example, Hendershott, Jones, and Menkveld (2008) use an instrumental variable to show that AT improves liquidity and makes quotes more informative. The results on AT liquidity supply and demand being more informed are the natural mechanism by which AT would lead to more informationally efficient prices.

Any analysis of AT relates to models of liquidity supply and demand.[3] Liquidity

[3] Parlour and Seppi (2008) for a general survey on limit order markets.

supply involves posting firm commitments to trade. These standing orders provide free-trading options to other traders. Using standard option pricing techniques, Copeland and Galai (1983) value the cost of the option granted by liquidity suppliers. The arrival of public information can make existing orders stale and can move the trading option into the money. Foucault, Roëll, and Sandas (2003) study the equilibrium level of effort which liquidity suppliers should expend in monitoring the market to avoid this risk. AT enables this kind of monitoring and adjustment of limit orders in response to public information,[4] but AT can also be used by demands to pick off liquidity suppliers who are not fast enough in adjusting their limit orders with public information. The monitoring of the state of liquidity in the market – leading to taking it when cheap and making it when expensive – is entirely consistent with AT playing an important role in the make/take liquidity cycle modeled expounded by Foucault, Kadan, and Kandel (2008).

AT is also used by traders who are trying to passively accumulate or liquidate a large position. Bertsimas and Lo (1998) find that the optimal dynamic execution strategies for such traders involves optimally braking orders into pieces so as to minimize cost.[5] While such execution strategies pre-dated wide-spread adoption of AT (cf. Keim and Madhavan (1995)), brokers now automate the process with AT products.

For each component of the larger transaction, a trader (or algorithm) must choose the type and aggressiveness of the order. Cohen et al. (1981) and Harris (1998) focus on the simplest static choice: market order versus limit order. If a trader chooses a non-marketable limit order, the aggressiveness of the order is determined by its limit price (Griffiths et al. (2000) and Ranaldo (2004)). Lo, MacKinlay, and Zhang (2002) find that execution times are very sensitive to the choice of limit price. If limit orders do not execute, traders can cancel them and resubmit them with more

[4]Rosu (2009) develops a model that implicitly recognizes these technological advances and simply assumes limit orders can be constantly adjusted.

[5]Almgren and Chriss (2000) extend this by considering the risk that arises from breaking up orders and slowly executing them.

aggressive prices. A short time between submission and cancelation suggests the presence of AT, and in fact Hasbrouck and Saar (2008) find that a large number of limit orders are canceled within two seconds on the INET trading platform (which is now Nasdaq's trading mechanism).

5.3 Data Matching and Preparation

The data was received directly from the DB and do not include human orders, i.e. only data from participants in the ATP. To identify human generated trades, algorithmic trades are matched with the public record of all trades and quotes provided by SIRCA. All publicly-reported trades that cannot be matched to the proprietary DB AT data are categorized as human trades. The combined data include security symbol, price, trade size, execution date and time. The focus is on the continuous trading phase by removing entries occurring during the opening, closing, intra-day, and volatility interruption auctions. To ensure a uniform data set across all analyses, the first fifteen minutes and the final five minutes are removed. All internalized retail trades are removed due to variable trade reporting lags allowed by the system[6].

AT trades are matched with trades in the SIRCA public data record. The best (highest bid and lowest ask) AT orders are matched with the SIRCA public order book. Using the AT order data, AT liquidity demanding trades are identified in the public data. Liquidity demanding trades are identified by matching the modification and entry time stamps. The identified AT trades are matched to the SIRCA trade data using the following criteria:

- Symbol
- Price
- Size

[6]The Deutsche Boerse offers a trade internalization system for retail orders called Xetra Best

- Trade Direction
- Time stamp (milliseconds)

Matches between the data sources identify liquidity-demanding trades (AT). Liquidity-demanding trades match exactly the trade size and price in the public data. The the trade initiator is identified in the SIRCA public data using the Lee and Ready trade direction algorithm (Lee and Ready (1991)) with the Bessembinder (2003b) modifications to determine the trade direction in the public data and use the modification and execution time stamp in the AT data.

Adjustments are made for an additional lag in the time stamp between the AT and SIRCA data sets. The publicly-available data is time stamped to the millisecond but, due to transmission and additional system processing, it lags the system order data. A time window of up to 500 ms is allowed in the public data when looking for a match of the remaining criteria. Table 5.1 below, summarizes the lags needed to match trades by type. The table makes clear that more than 75% of the trades match in the first 150 ms. The remaining trades match by 500 ms. A typical observation is that trades that match after more than 250 ms are transacted during high levels of market activity, which causes a system lag.

Table 5.1: Trade Matching by Type and Lag: This table reports the matches by lag. When no AT was involved in a trade AT Type is 'No ATP Participation'. Lag is in milliseconds and is the window between time-stamp in the Deutsche Boerse System Order data and SIRCA public data used for matching.

Lag (MS)	AT	% of Total
000-050	324600	25.62%
051-100	390456	30.82%
101-150	270765	21.37%
151-200	130655	10.31%
201-250	76999	6.08%
251-300	58765	4.64%
301-500	14561	1.15%
Total	1266801	100.00%

Matches of non-marketable orders submitted by algorithms are also made. In order to perform the information shares analysis (Hasbrouck (1995)) and study the difference between human and AT spreads, two order books are created. An AT order book using DB-ATP system order data is re-created using the system order data. To create a human order book, the SIRCA publicly disseminated order book is 'subtracted' from the AT order book. The SIRCA order book is disseminated with a lag, in this case not more than 250ms. This maximum lag was discovered by manual inspection of a large number of AT orders and SIRCA order books, especially around periods of high activity. After the AT order book is created, the best AT price and quantity is matched with the next order book update after the 250ms lag. If there were no updates within 500ms, the last update before 250 ms is matched. If a match is made and the AT price is 'better' than the posted price, the AT record is deleted. If the quantity match isn't exact, the AT quantity is adjusted to the lowest possible AT quantity. By performing these corrections AT are essentially handicapped, thereby giving the benefit of the doubt to humans in general.

See the following time line for a visual depiction of the matching process.

$0ms$	$100ms$	$250ms$	Reported	Actual
$AT_{t-1} \rightarrow 50$	$Hum_t \rightarrow 50$	$AT_{ob} - SIRCA_{ob}$	$Hum \leftrightarrow AT$	$AT \rightarrow Hum$

In the above case, an algorithmic trader submits a bid (buy) order at time $t-1$. At time t, 100ms in the future, a human submits an order for the same price 50. At time $t+1$, 250ms in the future, the AT order book AT_{ob} is compared with the next SIRCA order book $SIRCA_{ob}$. The AT_{ob} contains the AT order at time $t-1$. The $SIRCA_{ob}$ contains the AT_{t-1} order and the Hum_t order. In this scenario AT and hum orders are reported as occurring simultaneously. Clearly, however, this is not the case.

If the scenario is reversed i.e. hum_{t-1} and AT_t - the $SIRCA_{ob}$ is reported for time $t-1$ and the AT order is associated with a $SIRCA_{ob}$ at least 250ms in the future, and after the order book dissemination from hum_{t-1}. In this case, the ordering is correctly reported as hum_{t-1} and AT_t. The above matching scenario ensures that the most conservative approach to measuring AT information is taken.

5.4 Descriptive Statistics

The data provided by DB contain all AT orders submitted in DAX, the leading German stock market index composed of the 30 largest and most liquid stocks, for the 13-day trading period between January 1st and January 18th, 2008. Table 5.2 describe the 30 stocks in the DAX index. Market capitalization is as of December 31st, 2007 in billions of Euros. The smallest firm (TUI AG) is large at 4.81 billion Euros but is more than 20 times smaller than the largest stock in the sample, Siemens AG. The standard deviation of daily returns is calculated for each stock during the sample period. All other variables are calculated daily during the sample period for each stock (30 stocks for 13 trading days for a total of 390 observations). Means and standard deviations along with the minimum and maximum values are reported across the 390 daily observations.

DAX stocks are quite liquid. The average trading volume is 250 million euros per day with 5,344 trades per day on average. The number of trades per day implies that the data set contains roughly 2 million transactions (5,344*390). Quoted half-spreads are calculated when trades occur. The average quoted half-spread of 2.98 basis points is comparable to large and liquid stocks in other markets (see Hendershott and Moulton (2007)). The effective spread is the absolute value of the difference between the transaction price and the mid-quote price (the average of the bid and ask quotes). Average effective spreads are only slightly larger than quoted spreads, evidence that market participants seldom submit orders for depth at greater than the best bid or ask.

Depth is measured in two ways. The first is the standard measure of the depth

Table 5.2: Summary Statistics: This table presents descriptive statistics for the 30 constituents of the DAX index between January 1st 2008 and January 18th 20008. The data set combines Deutsche Boerse Automated Trading Program System Order Market and SIRCA trade, quote and order data. Market Capitalization data is gathered from the Deutsche Boerse website and cross-checked against data posted directly on the company's website and is the closing market capitalization on December 31st, 2007. All reported value are calculate per stock and day (390 observations) and report the mean, std. dev., maximum and minimum of these.

Variable	Mean	Std. Dev.	Min	Max
Mkt. Cap. (Euro Billion)	32.85	26.03	4.81	99.45
Price (Euros)	67.85	42.28	6.45	155.15
Std. Dev of Daily Return (%)	3.12	1.40	1.47	9.29
Daily Trading Volume (Euro Million)	250	217	23	1,509
Daily Number of Trades per Day	5,344	3,003	1,292	19,252
Trade Size (Euro)	40,893	15,808	14,944	121,710
Quoted Spread (bps)	2.98	3.01	1.24	9.86
Effective Spread (bps)	3.49	3.05	1.33	10.05
Depth (Euro 10 Million)	0.0177	0.0207	0.0044	0.1522
Depth3 (Euro 10 Million)	0.1012	0.1545	0.0198	1.0689

at the inside quote: the average depth in euros at the best bid price and the best ask price. As with spreads, depth is measured at the time of transaction. More depth allows traders to execute larger trades without impacting the price, which corresponds to higher liquidity. However, if the width of the spread varies over time, then comparisons of depth at the inside do not clearly correspond to levels of liquidity, e.g., 50,000 euros at a 20 basis point spread need not represent more liquidity than 5,000 euros at a 5 basis point spread if in the latter case there is additional depth between 5,000 and 50,000 euros. To account for time variation in the spread, a second depth measure is calculated using the limit order book. For each stock, the depth at bid and ask prices is aggregated that have a distance of less than three times that stock's average quoted half-spread from the midpount at the time of transaction. This measure of depth, which does not depend on the spread at the time of the transaction, is referred to as depth3. A similar measure was used in Foucault and Menkveld (2008) to capture depth away from the best.

5.5 AT Liquidity Demand

To measure AT liquidity demand, an AT trade-initiation variable AT and a human trade-initiation variable Hum are created. The AT variable takes the value 1 when a trade is initiated by an algorithmic trader, and 0 otherwise. The Hum variable takes the value 1 when a trade is initiated by a human and 0 otherwise. Panel A of Table 5.3 reports the fraction of euro trading volume for AT trades by trade size and overall.[7] Overall, AT initiate 52% of euro volume and more than 60% of all trades. AT initiation declines with trade size. AT is greater than 68% and 57% in the two smallest trade size categories (0-499 shares and 500-999 shares) and decreases to 23% in the largest trade size category (10,000+ shares). AT's decline with trade size is consistent with AT being used to breakup large orders into smaller trades as suggested by Bertsimas and Lo (1998).

To better understand the nature of AT and human liquidity demand, a series of analyses are performed, similar to those found in Biais, Hillion, and Spatt (1995). The results of the two separate and related analyses can be found in Table 5.4. Given the fraction of AT and human trades, the first column of Panel A of Table 5.4 (labeled *Unconditional*) provides the fraction of trades sequences, i.e., AT followed by AT, AT followed by human, etc., one would expect if AT and human trades were randomly ordered. The other columns in Panel A are essentially a contingency table documenting the probability of observing a trade of a specific type after observing a previous trade with a given type. All rows sum to 100% and can be interpreted as probability vectors.

[7]For simplicity and comparability the U.S. SEC Rule 605, trade size categories based on the number of shares traded is used.

Table 5.3: Trade Breakdown by Trade Size Category: AT is equal to one if a trade is initiated by an AT and zero otherwise. Hum is equal to one if a trade is initiated by a human and zero otherwise. Panel A reports volume weighted participation in 5 SEC trade size categories. Panel B reports the similar breakdown in percentage of total order flow by AT and humans.

Panel A Trade-size Categories	Trade Breakdown Participant AT	 HUM	 All
0 - 499	68%	32%	21%
500 -999	57%	43%	43%
1,000 - 4,999	42%	58%	21%
5,000 - 9,999	30%	70%	7%
10,000 +	23%	77%	8%
All	52%	48%	100%

Panel B Trade-size Categories	 Volume	 AT %Tot	by Trade Size Only HUM %Tot	 AT %Self	 HUM %Self
0 - 499	21.42%	14.6%	6.8%	28.2%	14.1%
500 -999	42.98%	24.6%	18.4%	47.5%	38.2%
1,000 - 4,999	20.64%	8.7%	11.9%	16.8%	24.8%
5,000 - 9,999	7.41%	2.2%	5.2%	4.2%	10.8%
10,000 +	7.56%	1.7%	5.9%	3.3%	12.2%
All	100.00%	51.9%	48.1%	100.0%	100.0%

Table 5.4: Trade Frequency Conditional on Past Trade: Panel A reports the conditional frequency of observing specific trades after observing trades of other participants. In column and row headings t indexes trades. AT represents AT trades and Hum represents human trades. In Panel B the three highest values per column are highlighted in bold.

Panel A Ordering	Unconditional	Frequency	Buy	Sell	$Buy_{t-1}Sell_t$	$Sell_{t-1}Buy_t$
$AT_{t-1}AT_t$	37.03%	40.73%	13.73%	10.96%	7.84%	8.20%
$AT_{t-1}HUM_t$	23.82%	20.12%	5.53%	5.05%	5.44%	4.11%
$HUM_{t-1}AT_t$	23.82%	20.12%	6.45%	5.64%	3.89%	4.15%
$HUM_{t-1}HUM_t$	15.33%	19.02%	5.48%	5.35%	3.75%	4.45%
		100.00%	31.18%	27.00%	20.91%	20.91%

Panel B	AT_t^5	AT_t^4	AT_t^3	AT_t^2	AT_t^1	Hum_t^5	Hum_t^4	Hum_t^3	Hum_t^2	Hum_t^1
AT_{t-1}^5	**8.38%**	**9.46%**	**18.13%**	16.78%	7.81%	**8.16%**	**6.03%**	6.74%	7.96%	10.54%
AT_{t-1}^4	**3.82%**	**7.87%**	**15.97%**	23.33%	11.71%	**4.51%**	4.61%	7.36%	9.90%	10.94%
AT_{t-1}^3	1.35%	2.73%	12.00%	**28.95%**	20.69%	2.22%	2.70%	6.23%	11.11%	12.03%
AT_{t-1}^2	0.22%	0.70%	4.69%	**27.10%**	**33.88%**	0.60%	1.12%	4.07%	11.89%	15.72%
AT_{t-1}^1	0.05%	0.18%	1.75%	16.67%	**48.70%**	0.17%	0.45%	2.19%	9.89%	19.94%
Hum_{t-1}^5	**5.46%**	**6.51%**	**13.72%**	17.50%	8.30%	**10.26%**	**7.15%**	**8.66%**	10.35%	12.09%
Hum_{t-1}^4	1.80%	3.36%	10.40%	22.56%	14.42%	4.24%	**6.40%**	**9.77%**	13.46%	13.58%
Hum_{t-1}^3	0.56%	1.39%	6.78%	**23.53%**	21.17%	1.70%	2.75%	**10.16%**	**16.36%**	**15.60%**
Hum_{t-1}^2	0.20%	0.54%	3.43%	19.21%	28.37%	0.69%	1.31%	4.95%	**19.83%**	**21.47%**
Hum_{t-1}^1	0.15%	0.34%	2.20%	14.98%	**33.10%**	0.56%	0.88%	3.36%	**13.92%**	**30.50%**
Unconditional	0.39%	0.73%	3.39%	17.10%	31.62%	1.03%	1.03%	3.88%	15.08%	26.18%

The first column and row of Panel A in Table 5.4 shows that if AT and human trades were randomly ordered, 37.03% of the transactions would be AT followed by AT, while in the data this occurs 40.73% of the time. The results show that AT trades are more likely than expected to follow AT trades and that AT trades are more likely to be repeated on the same side of the market. The same is not true for human trades. This suggests that the human and AT liquidity demanding trading strategies differ.

Panel B breaks the data down into AT and humans trade by trade size category. As in Biais, Hillion, and Spatt (1995), the three largest values in a column are highlighted in bold. The results attained are similar to the diagonal results reported in Biais, Hillion, and Spatt (1995) and predicted theoretically in Parlour (1998). The diagonal finding implies that trades of the same type – AT or human trades in the same trade size category – follow other similar trades. This is illustrated in the data, wherein the highest probabilities lie on the diagonal. The largest probability by far is for small AT trades: the $AT^1_{t-1}AT^1_t$ probability of 48.70% is much higher than the unconditional probability of 31.62%. This suggests that AT are repeatedly using small trades to hide their information or limit their transitory price impact, or that multiple AT are following related strategies. Panel B also shows that AT seem to be sensitive to human order flow whereas humans are relatively insensitive to AT order flow.

Table 5.5 reports the probability of observing an AT or human trade conditional on the spread of the previous trade. The quoted spread quartiles are calculated using the time series average of each stock. AT are more likely to submit a liquidity demanding trade after observing a small spread on a previous trade. The difference between the unconditional probability and conditional probability is statistically significant at the 1% level. From a statistical viewpoint, humans are significantly less likely to submit a liquidity demand trade after directly observing a trade with a small spread.

Table 5.5: Trade Frequency Conditional on Spread and Previous Time Interval: This table reports the conditional frequency of observing AT or human trades directly after observing trades with certain previous spreads or time intervals. In the columns Prob. AT and Prob. Hum the probability of observing a human or AT trade is expressed in percent. The t-stat is calculated using a double clustered standard error Thompson (2006).

Conditional on:	Prob. AT	t-stat H0: > Cond. Freq.	Prob. Hum	t-stat H0: > Cond. Freq.
Large Spread	56.80%	-47.07	43.20%	47.07
Medium Spread	59.16%	-20.37	40.84%	20.37
Small Medium Spread	61.73%	10.8	38.27%	-10.8
Small Spread	65.72%	61.41	34.28%	-61.41
Large previous time interval	60.06%	13.2	39.94%	-13.2
Small previous time interval	61.49%	-11.19	38.51%	11.19

It is plausible that humans react similarly to previous trades, but with a delay. The results are similar for the conditional probability of observing an algorithmic or human trade after a small or large previous time interval. AT are more likely to submit trades directly following small previous time intervals. The difference is statistically significant but has little practical impact.

Tables 5.4 and 5.5 provide trading frequencies based on prior trades and spreads, but is not informative on how closely together those events cluster. Table 5.6 reports the average time between trades dependent on past trades and spreads. As in Biais, Hillion, and Spatt (1995), spreads are calculated for each stock, and categories (e.g., large spread) are determined relative to averages/percentiles for that stock. For example, large spread represents trades in a stock that occur when spreads are in their widest quartile for that stock.

Table 5.6: Average Waiting Time Between Trades: The average amount of time between different trades is calculated. In Panel A the amount of time between two trades, two AT trades, and two human trades is reported. In Panel B these trades are broken-down into three trade size categories. The large trade-size category includes all trades > 1,000 shares. In Panel C the average waiting time is reported between trades conditional on the previous spreads. AT - Hum is the difference in waiting times for humans and AT. The t-stat tests the $H0$: that the difference is zero. A double-clustering technique is used on time and stock to calculate standard errors (Thompson, 2006). The Small - Large row reports the difference in waiting time between trades following small spreads and trades following large spread. The t-stat in the Diff Small - Large row tests the difference between small spread - large spread for AT - the average waiting time for small human spreads - average waiting time after large spreads. Spread categories are calculated as the time series average per stock.

Panel A		Avg. Time			
	Unconditional	ATAT	HumHum		
Unconditional	5.49	6.78	9.27		
Panel B		Avg. Time			
Size and Ordering	Trade → AT	AT → Trade	Trade → HUM	Hum → Trade	
Any Size	4.86	5.48	6.49	5.52	
Large	5.11	4.85	6.83	4.46	
Medium	5.04	5.17	6.34	4.89	
Small	4.73	5.72	6.49	6.19	
Panel C		Avg. Time			
Conditional on Spread	Unconditional	AT	Hum	AT - Hum	t-stat
Large Spread	6.89	9.03	11.43	-2.40	-15.46
Large medium spread	6.33	8.29	11.31	-3.01	-22.81
Small medium spread	5.05	6.72	9.96	-3.24	-35.57
Small spread	3.72	4.67	9.09	-4.42	-39.59
Diff Small - Large	-3.17	-4.36	-2.34	-2.02	-77.97
t-stat		-38.73	-15.53		

The most interesting results in Table 5.6 are in Panel C. When spreads narrow, the time until the next AT trade shrinks significantly from 9.03 seconds for large spread to 4.67 seconds for small spreads. While humans also respond more quickly to smaller spreads, the difference between large spread (11.43 seconds) and small spreads (9.09 seconds) is 2.34 seconds for humans versus 4.36 seconds for AT. The difference-in-differences of 2.02 seconds between AT large-spread minus AT small-spread and human large-spread minus human small-spread is statistically significant. This is further evidence that AT actively monitor the market for liquidity.

Thus far, AT and human sensitivity to past trades and spreads have been analyzed. Next, AT and human trading are investigated, taking into account contemporaneous and lagged liquidity measures. Following Barclay, Hendershott, and McCormick (2003a), similar liquidity variables are used and summarized in Table 5.2, including past return volatility and trading volume. Lagged volatility is the absolute value of the stock return over the 15 minutes prior to the transaction. Lagged volume is the euro trading volume in the 15 minutes prior to the transaction.

The correlation between the various measures of depth and liquidity and the AT activity variable and are presented in Table 5.7.

Table 5.7: Correlation of Order Flow, Liquidity and Depth: This table presents the overall correlation of the variables used in the Probit analysis. AT takes the value one when a trade is initiated by an AT and zero otherwise. Lagged volatility and volume are 15-minute lagged. Depth is the depth (price * shares) at the bid + the depth at the ask. Depth3 is the depth at three times the average quoted spread on the bid side + depth at three times the average spread on the ask side. Lagged volatility is the absolute value of the stock return over the past 15-minutes. Lagged volume is the sum of the volume over the past 15-minutes.

	AT	Quoted Spread	Effective Spread	Depth	Depth3	Lagged Volatility	Lagged Volume
AT	1.000						
Quoted Spread	-0.080	1.000					
Effective Spread	-0.094	0.928	1.000				
Depth	-0.047	-0.010	-0.017	1.000			
Depth3	-0.048	0.127	0.111	0.628	1.000		
Lagged Volatility	0.008	-0.047	-0.061	0.007	0.036	1.000	
Lagged Volume	-0.045	-0.120	-0.095	0.140	0.135	-0.167	1.000

All values sig. at 5% level.

AT activity correlates negatively and significantly with quoted and effective spreads. This is first evidence that AT is sensitive to liquidity variables. The hypothesis is tested in a more in-depth and robust probit analysis below.

Table 5.8 reports coefficient estimates from probit regressions for AT initiated trades along with their corresponding linear probability slopes and chi-square statistics. To control for stock effects and time of day effects, firm dummy variables (30) and 17 time-of-day dummy variables one for each half-hour period, are included but not reported. The only significant time-of-day effects are that AT becomes less likely at the end of the trading day, primarily in the last half hour of continuous trading. All $2,085,233$ observations (each trade in the data set) are used. A chi-square statistic of more than 3.84 represents statistical significant at the 5% level.

The probit results generally show that AT is more likely to trade when spreads are narrow and when trading volume over the prior 15 minutes is low. As in Panel A of Table 5.3, larger trades are less likely to be initiated by AT. Volatility over the prior 15 minutes is unrelated to AT. Once market conditions are controlled for, depth at the inside is unrelated to AT. Depth measured independently of the inside spread (depth3) is positively related to AT. The positive relation between AT initiation and liquidity and the zero relation between AT initiation and lagged volatility provide no evidence to support the contention that AT exacerbates volatility.

As with the spread results in the time until the next transaction analysis in Table 5.6, the depth and spread results establish that AT are more likely to initiate trades when liquidity is high. AT closely monitoring the book could bring about this result for two reasons. First, AT could time their liquidity demand for periods when liquidity is cheap, as in the Foucault, Kadan, and Kandel (2008) make/take liquidity cycle. When liquidity is expensive, algorithms simply wait until more liquidity is available before initiating a trade. A variant on this is that when liquidity is expensive, algorithms attempt to capture rather than pay the spread by switching from demanding liquidity to supplying liquidity, which is explored in Section 5.7.

Table 5.8: Probit Regression AT: The dependent variable is equal to one if the trade is initiated by an AT and zero otherwise. Trade size is the euro volume of a trade divided by 100,000. Depth is the depth (price * shares) at the bid + the depth at the ask. Depth3 is the depth at three times the average quoted spread on the bid side + depth at three times the average spread on the ask side. Lagged volatility is the absolute value of the stock return over the past 15-minutes. Lagged volume is the sum of the volume over the past 15-minutes. Firm fixed effects dummies and dummies for each half-hour of the trading day are not reported.

Variable	Model A	Model A1
Quoted Spread	-0.016	-0.016
– Probability Slope	-0.006	-0.006
– Chi-square	5324	5420
– Robust t-stat	-9.77	-10.37
Trade Size	-0.20	-0.20
– Probability Slope	-0.08	-0.08
– Chi-square	19645	19275
– Robust t-stat	-23.22	-22.74
Depth	-	-0.04
– Probability Slope	-	-0.01
–Chi-square	-	1.14
– Robust t-stat	-	-0.28
Depth3	0.10	-
– Probability Slope	0.04	-
–Chi-square	69	-
– Robust t-stat	0.91	-
Lagged Volatility	-0.648	0.161
– Probability Slope	-0.250	0.062
– Chi-square	0.07	0.00
– Robust t-stat	-0.04	0.01
Lagged Volume	-0.040	-0.030
– Probability Slope	-0.016	-0.012
– Chi-square	30.176	17.030
– Robust t-stat	-0.33	-0.14
Observations	2,085,233	2,085,233

The results suggest that AT monitor the market for liquidity and consume liquidity when it is cheap. This suggests that AT helps smooth out liquidity over time. When humans are more willing to supply liquidity, AT increase their liquidity demand. This, together with *AT* having no relationship to past volatility, suggests that AT is more likely to dampen than to increase volatility.

5.6 AT Liquidity Demand and Price Discovery

Having established that AT liquidity demand relates to liquidity dynamics, the dynamics between AT and returns is further examined. Just as AT monitor the market for variation in liquidity, AT may be able to process and act on information before humans can. This is examined by estimating the information content of AT and human events using Hasbrouck (1991a) and Hasbrouck (1991b) VARs.

5.6.1 Information Content of AT

To measure the information content of AT and human events, the permanent price impact of AT and human trading is calculated. Several papers have addressed related questions in multi-market settings; see for example Huang (2002) and Barclay, Hendershott, and McCormick (2003a) for quoting and trading on electronic communications networks and Nasdaq. In settings with multiple markets, variation in time stamps across markets make it difficult to ensure the proper ordering of events. In addition, if time stamps are only reported in seconds, trades and quote changes may occur contemporaneously. The data herein avoid these potential issues because trading is all within the DB Xetra system and time stamps are reported down to the millisecond. Therefore, the model is estimated on a event-by-event basis using 10 events in the future for AT and humans alike. The model is estimated for each stock for each day. Statistical inference is therefore performed using the 30 stocks * 13 days = 390 observations.

As in Barclay, Hendershott, and McCormick (2003a), three equations are estimated: a mid-point return (quote) equation; an AT trade equation; and a human trade equation. An event that is a trade or quote change is indexed using t as the time scale, q^{at} is defined as the signed (+1 for a buy, -1 for a sell) AT trades and q^{human} as the signed human trades. The quote midpoint is r_t and is defined as the quote midpoint to quote midpoint return between trades or quote changes. The

VAR using 10 events is as follows:

$$r_t = \sum_{i=1}^{10} \alpha_i r_{t-i} + \sum_{i=0}^{10} \beta_i q_{t-i}^{at} + \sum_{i=0}^{10} \gamma_i q_{t-i}^{human} + \epsilon_{1,t}, \tag{5.1}$$

$$q_t^{at} = \sum_{i=1}^{10} \delta_i r_{t-i} + \sum_{i=1}^{10} \rho_i q_{t-i}^{at} + \sum_{i=1}^{10} \zeta_i q_{t-i}^{human} + \epsilon_{2,t}, \tag{5.2}$$

$$q_t^{human} = \sum_{i=1}^{10} \pi_i r_{t-i} + \sum_{i=1}^{10} \upsilon_i q_{t-i}^{at} + \sum_{i=1}^{10} \psi_i q_{t-i}^{human} + \epsilon_{3,t}, \tag{5.3}$$

Each day the trading process restarts and all lagged values are set to zero. By estimating an event-by-event VAR, it is ensured that there is no correlation between q_t^{at} and q_t^{human}. After estimating the VAR model, Hasbrouck (1991a) and Hasbrouck (1991b) is followed and the VAR is inverted to get the vector moving average (VMA) model:

$$\begin{pmatrix} r_t \\ q_t^{at} \\ q_t^{human} \end{pmatrix} = \begin{pmatrix} a(L) & b(L) & c(L) \\ d(L) & e(L) & f(L) \\ g(L) & h(L) & i(L) \end{pmatrix} \begin{pmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \\ \epsilon_{3,t} \end{pmatrix},$$

where $a(L)-i(L)$ are the lagged polynomial operators. Following Hasbrouck (1991a), the impulse response function for AT is $\sum_{t=0}^{10} b(L)$ and can be interpreted as the private information content of an innovation in AT. Similarly, the impulse response function for humans is $\sum_{t=0}^{10} c(L)$. The impulse response functions provide an estimate of the permanent price impact of a trade innovation (the unexpected portion of a trade).

Table 5.9 reports the results of the impulse response function for 10 events into the future. The VAR is also estimated out to 100 events and no qualitatively different results are found. Table 5.9 reports impulse response functions for each of the 30 stocks and the average impulse response function across stocks. For each stock, the statistical significance of the impulse response function is estimated for AT and for human trading for the 13 trading days using Newey-West standard errors. AT has a greater permanent price impact for 28 of the 30 stocks and for 23 of those, the AT-human difference is statistically significant at the 5% level. The average permanent price impact for AT is 0.53 basis points versus 0.44 basis points for human trades. The statistical significance of this 0.09 overall difference is estimated between AT and human trades by double clustering standard errors on stock and trading day (Thompson (2006) and Petersen (2009)). In summary, an innovation in AT trading leads to a more than 20% greater permanent price change than an innovation in human trading.

Figure 5.1 graphs the overall average (across stock days) of the cumulative impulse response function of a positive (buy order) one standard deviation shock to AT and human order flow from the immediate response to 10 events in the future. The initial impact of an AT trade innovation is greater than for humans and the impact of AT versus humans trades increases over the subsequent 10 events. It can be seen that the impulse response function is becoming flat by the tenth event. Figure 5.1 shows that the price response to AT order flow is immediately greater than the response to human order flow.

Table 5.9: Average Long Run Impulse Response by Stock: This table reports the long-run (10 lag) impulse response function for AT and humans. The AT (Human) participation variable is equal to the trade direction (-1, 0, +1) multiplied by 1 if a trade is an AT (Human) initiated trade and zero otherwise. The reported mean is the mean difference between AT and Human impulse responses. The reported t-stat is calculated using Newey-West standard errors which are robust to autocorrelation across daily observations. Overall reports the mean of AT and human impulse response, in the AT-Mean column the average difference between AT and human impulse response functions is reported. A double-clustering technique is used on time and stock to calculate standard errors (Thompson, 2006).

Stock	AT	Human	AT-Human	t-stat
ADS	0.46	0.46	-0.01	-0.28
ALV	0.23	0.15	0.07	5.28
BAS	0.25	0.16	0.09	9.65
BAY	0.47	0.35	0.12	12.30
BMW	0.49	0.45	0.04	1.39
CBK	0.75	0.59	0.16	3.30
CON	0.51	0.39	0.12	5.16
DAI	0.36	0.28	0.09	4.33
DB1	0.46	0.39	0.07	6.62
DBK	0.30	0.25	0.05	2.12
DPB	0.52	0.40	0.12	3.90
DPW	0.57	0.56	0.01	0.22
DTE	0.96	0.82	0.14	1.57
EON	0.26	0.18	0.08	5.44
FME	0.52	0.45	0.08	1.51
HNK	0.61	0.49	0.12	2.08
HRX	0.76	0.74	0.02	0.33
IFX	1.42	1.25	0.17	1.18
LHA	0.84	0.68	0.16	2.99
LIN	0.33	0.36	-0.03	-1.59
MAN	0.49	0.36	0.12	3.50
MEO	0.55	0.39	0.16	3.99
MRC	0.54	0.43	0.11	3.40
MUV	0.29	0.20	0.10	3.58
RWE	0.35	0.23	0.12	3.65
SAP	0.43	0.31	0.11	2.92
SIE	0.25	0.20	0.06	2.43
TKA	0.58	0.40	0.18	5.88
TUI	1.17	0.90	0.26	4.63
VOW	0.31	0.22	0.09	8.99
Overall	0.53	0.44	0.09	8.71

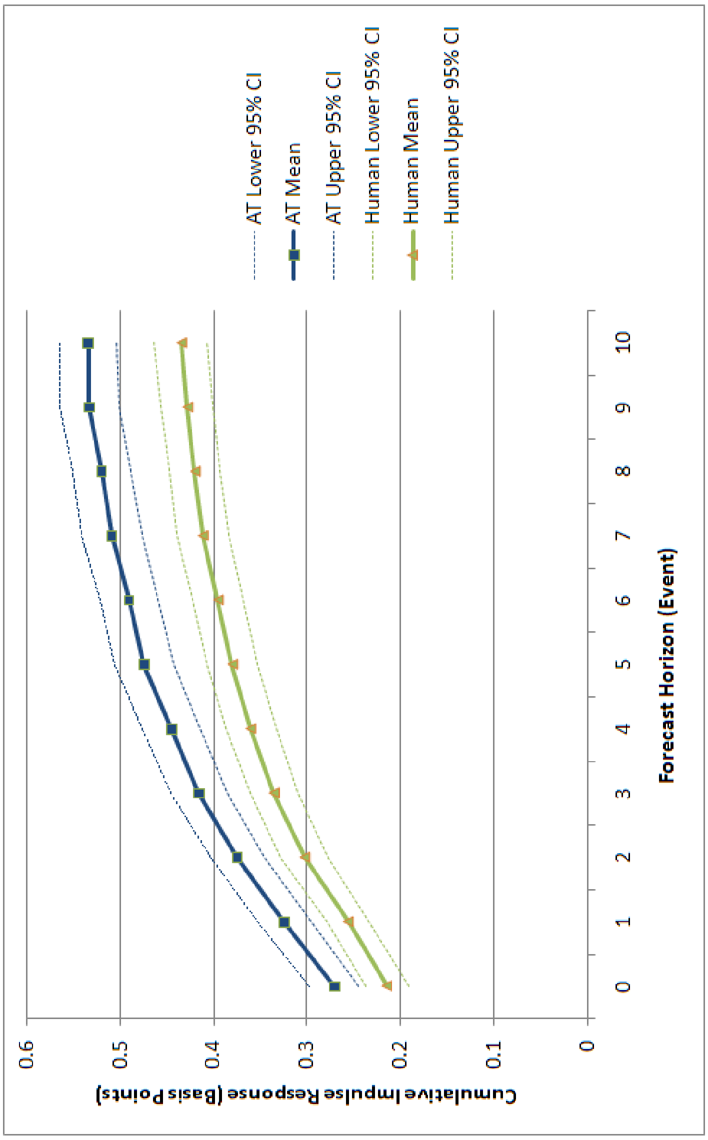

Figure 5.1: AT and Human Initiated Trades: This figure graphs the amount of trade-correlated information impounded into prices. The forecast horizon is on the X-axis from 0 to 10. The cumulative impulse response function in basis points is graphed on the y-axis.

The 95% confidence intervals in Figure 5.1 show that the larger immediate impact of AT is statistically significant. To calculate whether the lagged adjustment to AT is also greater, the difference between the long-run (LR; 10 event forecast horizon) and short-run (SR; immediate) impulse response functions is reported in Table 5.10. As in Table 5.9, the estimates for AT, humans, and the AT-human difference is reported for each stock and overall. The lagged adjustment (LR-SR) is smaller than the immediate response to trading for both AT and human trades. The LR-SR impulse response is greater for AT than for humans in 24 stocks. Seventeen of the AT estimates are statistically significantly greater than those for humans and in no stock is there statistical evidence that human trading has a larger impulse response function than does AT. The impulse response results provide evidence that individual innovations in AT have more private information than do human trades. This difference is persistent and increases beyond the immediate impact of the trade. If AT contributed to transitory volatility, the long-run impulse response function would be lower than the short-run impulse response function. The evidence is more consistent with AT playing an important role in the efficient price formation process.

Table 5.10: Long Run - Short Run Impulse Response: This table reports the long-run minus the short-run impulse response function for AT and human initiated trades, the difference between AT and human and the statistical significance of the difference. AT is the long-run (10 lag) impulse response minus the short-run (1 lag) impulse response for AT initiated trades, human is the long run (10 lag) impulse response minus the short run (1 lag) impulse response for human initiated trades. AT-Human is the difference between AT and Human impulse response functions. The t-stat is calculated using Newey-West standard errors which are robust to autocorrelation across daily observations. Overall reports the mean difference between the AT and human impulse responses. A double-clustering technique is used on time and stock to calculate standard errors (Thompson, 2006).

Stock	AT	Human	AT-Human	t-stat
ADS	0.20	0.22	-0.02	-0.59
ALV	0.09	0.06	0.03	2.25
BAS	0.13	0.07	0.05	8.22
BAY	0.22	0.16	0.06	4.57
BMW	0.23	0.24	-0.01	-0.95
CBK	0.26	0.21	0.04	0.71
CON	0.27	0.21	0.06	5.25
DAI	0.14	0.09	0.04	2.52
DB1	0.21	0.18	0.03	4.38
DBK	0.13	0.11	0.02	0.98
DPB	0.24	0.16	0.08	4.25
DPW	0.16	0.21	-0.05	-1.51
DTE	0.00	0.10	-0.10	-1.26
EON	0.13	0.08	0.04	3.66
FME	0.21	0.17	0.04	0.94
HNK	0.24	0.19	0.05	1.08
HRX	0.31	0.36	-0.05	-1.17
IFX	0.01	0.15	-0.14	-1.16
LHA	0.27	0.22	0.05	0.85
LIN	0.17	0.20	-0.03	-1.39
MAN	0.25	0.20	0.05	1.96
MEO	0.26	0.19	0.07	2.83
MRC	0.28	0.23	0.05	2.33
MUV	0.13	0.09	0.04	2.23
RWE	0.17	0.11	0.06	2.59
SAP	0.13	0.07	0.06	3.75
SIE	0.12	0.10	0.03	1.38
TKA	0.23	0.16	0.07	3.56
TUI	0.41	0.39	0.02	0.98
VOW	0.15	0.10	0.05	5.00
Overall	0.19	0.17	0.02	2.76

5.6.2 Aggregate Amount of Information in AT

The impulse response functions reported above provides evidence that innovations in AT have a significant impact on prices, but do not characterize how important the role of AT and human trading are in the overall price formation process. To do this, Hasbrouck (1991b) is followed in order to decompose the variance of the efficient price into the portion of total price discovery that is correlated with AT versus human trades. Doing this first requires decomposing the midpoint return r_t into its random walk m_t and stationary components s_t:

$$r_t = m_t + s_t \tag{5.4}$$

m_t is referred to as the efficient price where $m_t = m_{t-1} + w_t$ and $Ew_t = 0$; s_t is the transitory component. Using the previous VMA notation and defining $\sigma^2_{\epsilon_1} = E\epsilon^2_{1,t}$, $\sigma^2_{\epsilon_2} = E\epsilon^2_{2,t}$, and $\sigma^2_{\epsilon_3} = E\epsilon^2_{3,t}$, the variance of the efficient price is decomposed into trade-correlated and trade-uncorrelated changes.

$$\sigma^2_w = \left(\sum_{i=0}^{10} a_i\right)^2 \sigma^2_{\epsilon_1} + \left(\sum_{i=0}^{10} b_i\right)^2 \sigma^2_{\epsilon_2} + \left(\sum_{i=0}^{10} c_i\right)^2 \sigma^2_{\epsilon_3} \tag{5.5}$$

The second and third terms represent the proportion of the efficient price variance attributable to AT and humans, respectively. The first term is the public information (non-trade correlated) portion of price discovery.[8]

Table 5.11 reports the variance decompositions results. As in the previous analyses, the average by stock and overall is reported. In 27 of the 30 stocks, AT has a greater contribution to price discovery and in 21 of those stocks, the AT-human difference is statistically significant. In no stock is the human contribution to price discovery statistically significantly greater than that of AT. On average, AT

[8]Because each trade is initiated either by AT or by humans, the correlation in the trade equation residuals, $\epsilon_{2,t}$ and $\epsilon_{3,t}$, is zero. Because the contemporaneous trade variables are included in the return equation, the correlation of the residuals from the trade equations are uncorrelated with the residuals from the return equation. Therefore, the residual covariance terms in the variance decomposition are not included.

contributes 39% more to price discovery than do humans. The larger percentage difference between AT and humans for the variance decomposition as compared to the impulse response functions implies that the innovations in AT order flow are greater than are the innovations in human order flow. This is consistent with AT being able to disguise their trading intentions.

For brevity, the short-run (immediate) variance decomposition for AT and human trades is calculated but not reported. The results for the short-run variance decomposition are similar to those for the short-run impulse response functions in the previous section. Roughly half of the variance explained by AT and human trades is reflected immediately.

Table 5.11: Long Run - Variance Decomposition: This table reports the relative contribution of AT and human initiated trades, the contribution of non-trade related trade (r), the difference in contribution between AT and humans and the statistical significance of the difference. AT is the percentage of variance explained by AT initiated trades, human is the percentage of variation explained by human initiated trades, r is the percentage of variance explained by mid-point returns, the trade uncorrelated portion. AT-Human is the average difference in stock price variation explained by AT and humans. The t-stats is calculated using Newey-West standard errors which are robust to autocorrelation across across daily observations by stock. A double-clustering technique is used on time and stock to calculate standard errors for the overall difference (Thompson, 2006).

Stock	AT	Human	Return	AT-Human	t-stat
ADS	4.01%	4.50%	91.49%	-0.49%	-1.3
ALV	3.81%	2.01%	94.18%	1.80%	4.85
BAS	4.18%	1.81%	94.01%	2.37%	9.66
BAY	6.08%	3.69%	90.23%	2.39%	8.98
BMW	4.05%	3.95%	92.01%	0.10%	0.20
CBK	6.24%	4.06%	89.70%	2.18%	2.83
CON	5.23%	3.32%	91.45%	1.92%	4.88
DAI	4.23%	2.76%	93.01%	1.47%	3.15
DB1	6.05%	4.83%	89.12%	1.21%	4.45
DBK	4.29%	3.25%	92.46%	1.04%	1.93
DPB	4.10%	2.68%	93.23%	1.42%	2.56
DPW	4.54%	4.64%	90.82%	-0.0%	-0.15
DTE	12.71%	10.15%	77.13%	2.56%	1.03
EON	4.73%	2.51%	92.77%	2.22%	4.98
FME	5.06%	3.83%	91.11%	1.22%	1.35
HNKp	5.60%	4.70%	89.70%	0.90%	1.09
HRX	5.77%	5.42%	88.81%	0.35%	0.4
IFX	5.73%	5.67%	88.61%	0.06%	0.04
LHA	6.42%	4.52%	89.06%	1.90%	2.76
LIN	3.21%	4.01%	92.78%	-0.80%	-2.42
MAN	4.90%	3.01%	92.09%	1.89%	2.70
MEO	5.88%	3.31%	90.81%	2.57%	3.17
MRC	5.63%	4.11%	90.25%	1.52%	2.38
MUV	5.49%	2.89%	91.62%	2.59%	3.85
RWE	5.15%	2.56%	92.29%	2.59%	3.17
SAP	4.69%	2.76%	92.55%	1.94%	2.46
SIE	3.88%	2.76%	93.36%	1.13%	1.88
TKA	6.07%	3.28%	90.65%	2.79%	4.52
TUI	7.12%	4.93%	87.95%	2.19%	3.67
VOW	5.94%	3.24%	90.83%	2.70%	5.68
Overall	5.36%	3.84%	90.80%	1.52 %	8.01

5.7 AT Liquidity Supply and Price Discovery

The previous sections analyze AT-demanding liquidity and the role it plays in the price discovery process. Unfortunately, while the data from DB contains all transaction where AT supply liquidity, only 90% of these transaction can be identified unambiguously in the public transaction record.[9] This is due to the frequency of trading, the fact that the time stamps on the AT trades and overall trades are not identical, and because knowing the size of a non-marketable AT order does not uniquely identify the size of the total transaction. For example, if a non-marketable AT order of 100 shares is executed, the total trade size could be anything above 100 shares. There are often several possible trades that occur at times within plausible differences between the public transaction record and the AT transaction record.[10] Comparing the volume of executed non-marketable AT orders with the total trading volume shows that AT supply liquidity on 50% of trading volume.

While unable to make an exact match with AT liquidity supplying trades in the SIRCA public order book, an AT order book can be built and matched with the public order book. To understand how AT supply liquidity, two order books are built (see the Chapter 3 for further details). One AT order book is built that contains the best prices and sizes of AT orders and is then compared with the SIRCA full order book. The depth in the full SIRCA order book that is not found in the AT order book is the human order book. The inside bid and ask quotes is stored for the AT and humans. If there is any doubt, each step in the matching procedure assumes human quote updates occur before AT quote updates.

Whether or not AT are more likely to supply liquidity at the best quote is examined first. This provides initial evidence on whether or not AT are competitive

[9] Analysis on the transactions unambiguously identified as AT-liquidity-supplying supports the main findings in this section that AT supply liquidity when it is expensive and AT are less likely to trade against private information.

[10] Multiple feasible matches for AT transactions also occur for liquidity demanding trades. However, when AT initiates a trade, size is uniquely identified. This only occurs in 0.1% of the AT liquidity-demanding trades as opposed to 10% of the AT liquidity-supplying trades.

in quoting the best prices for marketable orders to trade with. Table 5.12 examines the amount of time AT and humans are at the inside bid and ask. This combines the times when AT and humans are alone at the inside and when they are both at the inside together. A positive number indicates that an algorithmic trader was at the best alone for longer than was the human trader, whereas the reverse is true if the value is negative.

Table 5.12 shows that AT are at the inside more often in 24 of the 30 DAX stocks, with the difference being statistically significant in 21 of the 24 stocks. On average, AT are at the inside almost 1 hour more per day than are humans, and that difference is statistically significant. Table 5.12 also examines whether or not AT are more likely to be present at the inside when spreads are wide or narrow. As in Table 5.6, times when spreads are wider and narrower than average for that stock are identified. The amount time during the high- and low-spread times that AT and humans are on the inside is calculated. Table 5.12 shows that AT are at the inside more often during both high- and low-spread periods, but the AT-human difference is significantly higher during the high-spread periods. This shows that AT are more likely to provide liquidity when liquidity is expensive. This is consistent with AT attempting to capture liquidity supply profits in the Foucault, Kadan, and Kandel (2008) make/take liquidity cycle.

The previous analysis of the amount of time AT and humans spend at the best bid or ask addresses the questions of how long and when each supply liquidity at the best. The analysis does not address the question of whether, on average, AT or humans supply tighter quotes. Table 5.13 reports the results of an analysis examining the average bid and ask quotes submitted by AT and humans.

Table 5.12: Time at Best: This table reports the number of seconds an AT is at the best - minus the number of seconds a human is at the best. The remainder of time both AT and humans are at the best. The first column reports the AT - Human time at best. T-stats are calculated using Newey-West standard errors for each stock and Thompson (2006) standard errors for the entire panel. The Q1 AT - Human column reports the average AT - Human time at best when spreads are below their per stock time series average. The Q2 AT - Human column reports the average AT - Human time at best when spreads are above their time series per stock average. Q1 - Q2 reports the difference between time at best below the time series quoted spread average - time at best above the time series quoted spread average.

Stock	AT - Human	t-stat	Q1 AT - Human	Q2 AT - Human	Q1 - Q2	t-stat
ADS	4,235	3.91	1,454	2,780	-1,326	-2.35
ALV	-3,000	-2.94	-2,368	-632	-1,735	-2.67
BAS	1,011	1.41	-492	1,503	-1,995	-6.07
BAY	3,136	6.44	718	2,418	-1,700	-10.58
BMW	6,321	4.31	2,612	3,708	-1,095	-1.83
CBK	4,706	2.95	2,996	1,709	1,287	2.1
CON	1,249	0.96	-739	1,988	-2,727	-8.01
DAI	-3,893	-2.27	-3,508	-385	-3,122	-14.16
DB1	2,739	4.94	132	2,607	-2,475	-2.88
DBK	-3,395	-8.58	-3,254	-141	-3,112	-8.51
DPB	7,115	7.83	2,187	4,927	-2,740	-6
DPW	4,555	4.76	2,789	1,765	1,024	2.83
DTE	-2,461	-3.56	-2,087	-374	-1,713	-3.9
EON	1,479	2.29	-301	1,780	-2,081	-5.59
FME	11,850	11.64	5,361	6,489	-1,128	-0.75
HNK	7,494	10.04	4,054	3,439	615	0.58
HRX	1,028	0.54	-722	1,751	-2,474	-5.04
IFX	-201	-0.22	-287	85	-372	-0.95
LHA	4,056	2.45	3,215	840	2,375	1.9
LIN	7,219	12.42	2,727	4,492	-1,764	-4.03
MAN	4,712	9.18	1,297	3,415	-2,117	-6.42
MEO	6,843	3.93	3,258	3,585	-326	-0.53
MRC	9,155	9.8	3,348	5,806	-2,457	-5.3
MUV	6,959	8.94	2,492	4,466	-1,974	-2.58
RWE	3,551	6.13	874	2,676	-1,802	-2.69
SAP	3,715	6.1	656	3,059	-2,402	-6.78
SIE	-1,911	-2.48	-2,612	701	-3,313	-11.73
TKA	4,238	14.51	883	3,354	-2,470	-6.35
TUI	5,885	5.26	4,082	1,802	2,279	3.16
VOW	2,415	2.27	-42	2,458	-2,500	-3.12
Overall	3,360	7.00	958	2,403	-1445	-7.21

Table 5.13: Full - AT - Human Spread: This table reports the average spread, average AT spread and average human spread. AT-Human is the difference between AT and human spread. The t-stat is calculated using Newey-West standard errors at the individual stock level. A double clustering technique is used on time and firm to calculate standard errors for the entire panel Thompson (2006) .

Stock	Full Spread	AT Spread	Human Spread	AT-Human	t-stat
ADS	3.51	4.46	4.89	-0.42	-2.68
ALV	1.49	2.37	1.96	0.41	6.23
BAS	1.76	2.49	2.38	0.11	1.46
BAY	2.29	3.02	3.17	-0.15	-4.50
BMW	2.76	3.71	4.26	-0.54	-3.07
CBK	4.05	5.25	5.77	-0.52	-1.96
CON	3.31	4.46	4.24	0.23	1.58
DAI	2.49	3.69	3.18	0.51	4.10
DB1	3.24	4.45	4.19	0.26	4.59
DBK	1.82	2.76	2.37	0.39	17.02
DPB	4.26	5.59	6.05	-0.45	-3.03
DPW	3.66	4.48	5.14	-0.66	-4.55
DTE	3.59	4.30	4.00	0.29	3.16
EON	1.58	2.23	2.12	0.11	3.38
FME	3.67	4.36	5.77	-1.41	-8.38
HNK	4.23	5.21	6.25	-1.06	-6.52
HRX	5.27	7.02	7.00	0.02	0.02
IFX	8.26	9.60	9.91	-0.31	-1.63
LHA	4.71	5.82	6.56	-0.75	-2.34
LIN	2.91	3.76	3.99	-0.22	-4.72
MAN	3.98	5.05	5.06	-0.01	-0.33
MEO	3.07	3.84	4.42	-0.58	-2.94
MRC	4.24	5.21	5.85	-0.64	-4.97
MUV	1.74	2.30	2.43	-0.13	-3.51
RWE	1.96	2.68	2.70	-0.03	-0.49
SAP	2.64	3.53	3.91	-0.38	-5.89
SIE	1.77	2.67	2.33	0.34	6.47
TKA	3.31	4.34	4.68	-0.34	-5.89
TUI	5.09	6.21	7.56	-1.35	-7.54
VOW	2.11	2.88	2.73	0.15	1.88
Overall	3.29	4.26	4.50	-0.24	-3.67

The results confirm the results of the time at best analysis and confirm that AT submit tighter spreads than humans and contribute positively to liquidity. The average difference between AT and human spreads is statistically significantly lower for 15 of 30 stocks and for the panel as a whole. Humans submit significantly tighter spreads in only seven of 30 stocks.

For AT to be on the inside more often yet only provide liquidity for for 50% of volume, AT orders must be smaller or times when humans are alone at the inside are more likely to have transactions. One natural explanation for trades occurring more often when humans are alone at the inside quote is that the human quotes are stale and are adversely picked off. By examining how much the AT and human quotes contribute to the price discover process we can show that AT and human quotes are different and that AT quotes better reflect the efficient price. If AT quotes contribute more to the price discovery process, human quotes may appear inaccurate and stale.

5.7.1 Hasbrouck Information Shares

To examine AT and human quotes in the price discovery process, the Information Shares (IS) approach pioneered by Hasbrouck (1995) is used. Typically this approach is used to determine which of several markets contributes more to price discovery. This approach has been used in the literature to compare spot and derivatives markets (e.g., Tse (1999) and Chan, Chung, and Fong (2002)) and multiple stocks market (Hasbrouck (1995), Huang (2002), Barclay, Hendershott, and McCormick (2003a), and others). Because the information share has been widely used, only some of the technical details are provided. The econometric approach assumes that AT and human quotes form a common efficient price process. The information share attributable to AT and human quotes is the relative contribution of the innovations of each to the innovation in the common efficient price. The general convention is to equate the proportional information share to price discovery.

Because AT and human quotes are for the same stock, arbitrage requires that the two price series be co-integrated. The AT mid-point is calculated as $MP_t^{AT} = (BestBid_t^{AT} + BestAsk_t^{AT})/2$ and the midpoint for humans is calculated in the same manner. The midquotes are assumed covariance stationary. The information share of a participant is measured as that participants contribution to the total variance of the common (random-walk) component. To formalize, denote a price vector p_t that represents the prevailing mid-quote for AT as $p_t^{AT} = m_t + \epsilon_t^{AT}$ and humans as $p_t^{Hum} = m_t + \epsilon_t^{Hum}$. m_t, the common efficient price is assumed to follow a random walk:

$$m_t = m_{t-1} + u_t, \tag{5.6}$$

where $E(u_t) = 0$, $E(u^2 t) = \sigma_u^2$, and $E(u_t u_s) = 0$ for $t \neq s$. The price vector can be represented using a VMA model.

$$\Delta p_t = \epsilon_t + \psi_1 \epsilon_{t-1} + \psi_2 \epsilon_{t-2} ..., \tag{5.7}$$

Where ϵ is a 2 X 1 vector of innovations with a zero mean and a variance matrix of Ω; $\epsilon_t = [\epsilon_t^{AT}, \epsilon_t^{Hum}]$ where ϵ_t^{AT} reflects the innovations (information) attributable to AT and ϵ_t^{Hum} that to humans. The variance of the random walk component is then:

$$\sigma_u^2 = \Psi \Omega \Psi' \tag{5.8}$$

where $\Omega = Var(\epsilon_t)$ and Ψ is a polynomial in the lag operator. Expanding the above equation yields:

$$\sigma_u^2 = [\Psi^{AT}, \Psi^{Hum}] \begin{bmatrix} \sigma_{at}^2 & \sigma_{at,hum} \\ \sigma_{hum,at} & \sigma_{hum}^2 \end{bmatrix} \begin{bmatrix} \Psi^{AT} \\ \Psi^{Hum} \end{bmatrix}.$$

If the covariance matrix is diagonal, then the random-walk variance attributable to AT and to humans can be perfectly identified. If the record of the public limit order book was updated every time an order arrived, there should be no contemporaneous correlation between AT and human quote changes. However, it appears that at times the public order book dissemination contains multiple updates. Thus the off-diagonal terms are not zero, and Hasbrouck (1995) is followed to construct upper and lower bounds for the information shares of AT and human quotes. The upper bound for AT corresponds to the assumption that all of the contemporaneous correlation between AT and human quote changes is attributable to AT, whereas the lower bound for AT assumes the contemporaneous correlation between AT and human quote changes is attributable to humans. Table 5.14 presents these estimates. As with the impulse response and variance decompositions for AT liquidity demand, the information shares are calculated each day. Tests of statistical significance are calculated based on the 13 days for each stock. For the overall estimates, the 390 stock day information share estimates are pooled to calculate standard errors controlling for correlation within each stock's estimate and controlling for correlation across stocks on the same day. It is worth recalling that the construction of the AT and human quotes ensured that whenever there was uncertainty as to whether or not an AT quote change preceded or followed a close by human quote change, it is assumed the human quote change occurred first. Therefore, the lower bound for the AT information share is truly a lower bound, but the upper bound for AT information share is a lower bound for the true upper bound.

Table 5.14: Hasbrouck Information Shares: In this table the Hasbrouck Information Shares are calculated for AT and humans. In Panel A the AT contribution is maximized by taking the AT first human second ordering. AT-Human reports the difference between AT and human contribution. The t-stat is calculated using Newey-West standard errors for each stock and Thompson (2006) standard errors for the entire panel. In Panel B the human first AT second ordering is rpeorted.

Panel A				
Stock	AT First	Hum Second	Diff	t-stat
ADS	0.58	0.42	0.16	3.53
ALV	0.56	0.44	0.12	2.9
BAS	0.53	0.47	0.07	1.55
BAY	0.71	0.29	0.41	22.64
BMW	0.65	0.35	0.31	2.74
CBK	0.58	0.42	0.17	1.46
CON	0.51	0.49	0.02	0.21
DAI	0.51	0.49	0.02	0.35
DB1	0.54	0.46	0.08	0.92
DBK	0.55	0.45	0.09	1.54
DPB	0.56	0.44	0.13	1.25
DPW	0.66	0.34	0.32	4.54
DTE	0.72	0.28	0.44	13.92
EON	0.53	0.47	0.07	1.25
FME	0.63	0.37	0.26	5.9
HNK	0.72	0.28	0.44	7.94
HRX	0.48	0.52	-0.04	-0.25
IFX	0.75	0.25	0.50	29.57
LHA	0.72	0.28	0.43	7.61
LIN	0.54	0.46	0.08	0.6
MAN	0.57	0.43	0.13	4.1
MEO	0.69	0.31	0.38	5.89
MRC	0.58	0.42	0.16	1.48
MUV	0.67	0.33	0.35	11.96
RWE	0.65	0.35	0.29	8.56
SAP	0.67	0.33	0.35	5.53
SIE	0.48	0.52	-0.04	-0.75
TKA	0.61	0.39	0.22	2.49
TUI	0.70	0.30	0.40	5.97
VOW	0.55	0.45	0.09	2.07
Overall	0.61	0.39	0.21	9.61

continued below ...

... continued from Table 5.14

Panel B				
Stock	AT First	Hum Second	Diff	t-stat
ADS	0.48	0.52	-0.03	-0.67
ALV	0.44	0.56	-0.12	-2.43
BAS	0.43	0.57	-0.13	-3.53
BAY	0.62	0.38	0.23	8.84
BMW	0.57	0.43	0.14	1.04
CBK	0.50	0.50	0.01	0.05
CON	0.43	0.57	-0.15	-1.75
DAI	0.41	0.59	-0.19	-2.36
DB1	0.42	0.58	-0.16	-2.44
DBK	0.42	0.58	-0.17	-3.35
DPB	0.46	0.54	-0.08	-0.79
DPW	0.58	0.42	0.17	2.17
DTE	0.54	0.46	0.08	1.15
EON	0.43	0.57	-0.13	-2.82
FME	0.58	0.42	0.16	3.5
HNK	0.65	0.35	0.31	5.36
HRX	0.41	0.59	-0.18	-1.28
IFX	0.64	0.36	0.27	5.51
LHA	0.65	0.35	0.29	4.73
LIN	0.45	0.55	-0.11	-0.85
MAN	0.47	0.53	-0.05	-1.37
MEO	0.60	0.40	0.19	3.78
MRC	0.50	0.50	-0.01	-0.07
MUV	0.58	0.42	0.15	4.47
RWE	0.55	0.45	0.09	2.89
SAP	0.62	0.38	0.24	3.61
SIE	0.41	0.59	-0.18	-3.14
TKA	0.56	0.44	0.11	1.3
TUI	0.61	0.39	0.21	2.86
VOW	0.44	0.56	-0.12	-2.25
Overall	0.51	0.49	0.03	1.22

Panel A reports the upper bound estimate for AT information shares and the lower bound for human information shares. Panel B reverses the ordering to provide the lower bound estimate for AT information shares and the upper bound for human information shares. The results in Panel A of Table 5.14 show that in 18 of 30 stocks, AT have statistically significantly higher information shares. For the entire panel, AT have a 21% higher information share, with a t-statistic of 9.61. In no stocks do humans have statistically significantly higher information shares than do AT. The same statistical framework is used as in the previous sections. In Panel B it can be seen that the lower bound for AT information shares is statistically significantly higher than the upper bound for humans in 11 stocks while the upper bound for humans is statistically significantly higher than the lower bound for AT in eight stocks. Overall, the lower bound on AT information shares is greater than the upper bound for human, but the difference is not statistically significant.

Comparing the upper and lower bounds on AT and human information shares in Panels A and B of Table 5.14 shows that 51% of price discovery comes from AT quotes, 39% of price discovery comes from human quotes, and 10% occurs contemporaneously in AT and human quotes. Given that the quote changes are ordered to favor the human role in price discovery, evidence supports AT playing a larger role in price discovery, but no evidence is seen suggesting that humans play a larger role.

5.8 Conclusion

Algorithmic trading is studied in terms of its role in the price formation process. It is found that AT consume liquidity when it is cheap and provide liquidity when it is expensive. AT contributes more to the discovery of the efficient price than does human trading. These results demonstrate that AT closely monitor the market in terms of liquidity and information and react quickly to changes in market conditions. Contrary to conventional wisdom, no evidence if found of AT behavior that would contribute to volatility.

The results have important implications for academics, regulators, and market operators. Theoretical models of limit order books should allow for a significant fraction of traders who closely monitor the market. These traders could prevent prices from deviating significantly from fundamentals and prevent spreads from widening beyond a certain point; both of these features would reduce the dimensionality of the state space (cf. Goettler, Parlour, and Rajan (2009)). The ATP approved by the German competition authority appears to have led to behavior that should improve both price efficiency and market liquidity in DAX stocks. However, as with most financial innovations, there is always the possibility that wide-spread use could eventually have unexpected negative consequences.

Chapter 6

Conclusion and Future Work

Potential advances in AT are surely not exhausted. Only recently have the possibilities of using algorithms to read news and economic releases begun. Information providers, such as Dow Jones and Thomson Reuters[1] and other specialty information providers have just begun to provide machine-readable news for algorithmic consumption. Other recent developments in the area of financial reporting, such as the Securities and Exchange Commission's[2] decision to make mandatory what was previously a voluntary pilot project to provide eXtensible Business Reporting Language (XBRL), are shaping the information landscape. XBRL is a standardized business reporting language that makes a firm's financial reports machine readable and available in real-time to markets. This program extension is being phased in over the next 12 months and will become mandatory for all filers by 2010. The implication of this and other similar projects worldwide are yet to be felt by AT and markets.

6.1 Future Work

The general direction, of information providers and regulators alike is to make information more accessible. The more accessible the information, the lower the cost to process it. The reduced cost and ease of access to information should translate into

[1]See: Dow Jones Elementized News Feed and Thomson Reuters NewsScope Sentiment Engine
[2]See: www.sec.gov - Spotlight on XBRL

more efficient prices. Making this information more accessible to AT (as well as human participants) is leading to a shift in competitive factors in the market. Humans cannot process information as quickly as algorithms but they can, however, expertly interpret information – especially complex textual information. These factors have yet to be studied in the literature.

With the increase in machine-readable information, the question will increasingly become ‘is this information new?’. Humans and AT will have to determine whether or not a news story or report is new information about a firm or information that is already reflected in prices. This became painfully obvious in a recent trading debacle involving United Airlines - ticker UAL. An old news story reporting that United Airlines was seeking Chapter 11 bankruptcy protection was erroneously processed as being new information. Algorithms using Google to cull new information ’saw’ the story and began selling UAL shares. Only after a drop of more than 60% did investors, Google and the exchange realize the problem was in the Google news algorithm and that a small change in the header of the old story at the South-Florida Sun Sentinel newspaper was the cause.

As the cost of technology further declines, the application thereof in the trading process will continue to increase. Even in the current economic crisis, AT has remained steady and has reportedly risen slightly recently. This raises a number of obvious questions, posed by regulators and participants alike. How will this increased automation affect trading costs, price discovery and competition in securities markets? What happens in a market where algorithms are the predominant traders but are highly sensitive to shocks. Do AT reduce or increase their trading activities? Are markets with more AT inherently more volatile and is such a situation realistic?

Some of these issues are being addressed directly in joint research projects within the Information and Market Engineering Graduate School. One study is looking into whether or not trading strategies based on high-frequency, sentiment-tagged news are profitable. Within this research project, there are plans to build an AT simulation system to test AT strategies but also to gauge their impact on the market as a whole.

6.2 Summary

This dissertation is one of the first to answer some of the important questions with regards to AT. The results herein show that AT are not nearly as bad as their reputation. No evidence is found that would suggest that AT contribute to transitory volatility. Evidence is found that shows that AT contribute positively to the liquidity supply and price discovery processes. Evidence is also found that AT act as both suppliers as well as consumers of liquidity. Their contribution to price discovery is critical. As markets and information become increasingly more complex and the sources of these less integrated, our ability to process all of the information for a specific stock or industry diminishes greatly. By using AT technologies, participants are able to process more information in a shorter period of time, thereby making prices more efficient.

Algorithmic traders also appear to contribute positively to liquidity. They are more likely to supply liquidity when it is dear and consume it when cheap, thereby smoothing it across time. They are more likely to be at the best for longer when spreads are wide, as spreads tighten they seem to shift from liquidity supply to liquidity demand. When spreads tighten, AT are more likely to demand liquidity by submitting marketable limit orders. This liquidity smoothing finding is quite novel in that it rejects common beliefs that AT contribute to market instability. There is no evidence to support the belief that AT contributes to market instability.

One point that was perhaps not stressed enough in the previous chapters is the human component of AT. In the preceding work, humans are often pitted against AT as if AT had no human component. AT systems are and will continue to be programmed, monitored, designed, fixed, and cursed by humans. An algorithm in financial markets is no different than a robot in a manufacturing setting. Both perform the tasks they are assigned until they are assigned new tasks. Certain is that in AT, humans will continue to play a dominant role. For the investment process this will hopefully lead to humans being able to spend more time on fundamental analysis and risk management and less time implementing their trading decisions.

Appendix A

ATP Agreement

ATP Agreement
for participation in the "Automated Trading Program" (ATP) via the electronic trading system Xetra®

DEUTSCHE BÖRSE

Deutsche Börse AG, Frankfurt am Main

and

____

- hereinafter referred to as "ATP member" -

hereby conclude the following Agreement.

§ 1 Object of the Agreement

The object of this Agreement is participation in Deutsche Börse AG's "Automated Trading Program" (ATP) by the ATP member. The following provisions apply to this Program. They do not affect the duties and rights arising from the ATP member's participation in the electronic trading System Xetra®.

§ 2 Definitions

(1) ATP transactions refer to all transactions that have been generated by an electronic system of either the ATP member or the ATP member's clients, whereby the electronic system has to determine two out of the three following order parameters: price (order type and/or order limit where applicable), timing (time of order entry) and quantity (quantity of the order in number of securities). As a principle, the number of ATP transactions should negatively correlate with the Xetra® transaction fee level i.e. reduced Xetra® transaction fees should systematically result in an increased number of ATP transactions. Furthermore ATP transactions must be channelled into the electronic trading system Xetra® using an ATP User-ID.

(2) The electronic system that generates the ATP transactions must fulfil the following requirements:

- The electronic system must generate buy or sell orders independently, i.e. without frequent manual intervention, using a specified program and data;
- The generated orders have to be channelled directly into the electronic trading system Xetra® without further manual intervention;
- The exchange fees or the fees charged by the ATP member to its clients have to be directly or indirectly considered by the electronic system when determining the order parameters.

ATP Agreement
for participation in the "Automated Trading Program" (ATP) via the electronic trading system Xetra®

DEUTSCHE BÖRSE

(3) The following types of transactions in particular are not classed as ATP transactions for the purposes of the ATP Initiative:

- Transactions that are channelled into the electronic trading system Xetra® using the Xetra® account types D (Designated Sponsor), E (Best Executor), I (Issuer) and L (Liquidity Provider);
- Transactions that are channelled into the electronic trading system Xetra® via order routing without originally being generated within the meaning of Section 2 (1) and (2).

(4) Introductory ATP Member shall mean any newly registered ATP member or any existing ATP member whose ATP trading volume has not qualified for an ATP rebate in the recent 24 months.

§ 3 ATP rebates

(1) ATP rebate rates as set out in the "Price List for the Utilization of the Trading System of the Frakfurt Stock Exchange" apply to ATP transactions within the meaning of Section 2 of this Agreement.

(2) ATP rebate rates as set out in the "Price List for the Utilization of the Trading System of the Frankfurt Stock Exchange" will not be included in the existing Xetra® fee reporting (e.g. trade confirmation, fee reports), but will only be taken into account for monthly invoicing purposes.

§ 4 Duties of the ATP member and Deutsche Börse AG

(1) In order to participate in the ATP Initiative, the ATP member undertakes to register one or more ATP User-IDs, which will be used exclusively for ATP transactions within the meaning of Section 2 of this Agreement and which will be under the responsibility of exchange traders approved by the Frankfurt Stock Exchange. The ATP member undertakes to register different ATP User-IDs for its own ATP transactions and for ATP transactions of the ATP member's clients. Registration is a prerequisite for participation in the ATP Initiative. The registration form "Application for the Approval of an ATP User-ID" attached to this Agreement must be used to register the ATP User-IDs.

(2) Upon registration of its ATP User-IDs, the ATP member undertakes to provide Deutsche Börse AG with a general description of the different types of ATP transactions of the ATP member as well as the ATP member's clients. The description has to be provided as laid out in the registration form "Application for the Approval of an ATP User-ID".

(3) The ATP member will undertake best efforts to ensure that all transactions of its clients that are channelled into the electronic trading system Xetra® using the ATP User-ID are within the meaning of Section 2 of this Agreement; the ATP member verifies and documents the compliance of its clients' transactions with Section 2 on a regular basis. If the ATP member suspects

or ascertains that orders of its clients do not comply with Section 2 he shall notify Deutsche Börse AG immediately thereof.

(4) Deutsche Börse AG will not disclose any confidential information about the ATP member or the ATP member's clients it may receive in connection with this Agreement to any third party, unless provided by this Agreement or required by law. The ATP member hereby authorizes Deutsche Börse AG to disclose the member's ATP User-IDs, the respective numbers of executed ATP orders in instruments cleared by Eurex Clearing AG and the respective ATP rebates to Eurex Clearing AG and Eurex Clearing AG is hereby authorized to disclose such data in the monthly invoicing to its Clearing Member which clears the ATP transactions of the ATP member. The ATP member hereby further authorizes Deutsche Börse AG to disclose information to the Frankfurt Stock Exchange's Trading Surveillance Office, to the extent that is necessary to monitor the ATP member's compliance with the duties incumbent upon it as a result of this Agreement.

§ 5 Term/Notice of termination

(1) The ATP Agreement runs for an indefinite period of time. Each party may terminate this Agreement with 3 months notice, with the effect as per the end of a calendar month.

(2) Deutsche Börse AG's right of extraordinary termination without notice for good cause shall remain unaffected hereby. Good cause shall in particular be given, if:

- the ATP member or its agents - despite a prior notice of default - commits a breach of material duties arising from this Agreement;
- there is a substantiated suspicion that the ATP member is using its registered ATP User-IDs for purposes other than for ATP transactions within the meaning of Section 2 of this Agreement. In the latter case, Deutsche Börse AG has the additional right to abstain from its extraordinary termination right and instead suspend the ATP member from participating in the ATP initiative for the suspicious period of time.

(3) The ATP member shall have a right of extraordinary termination without notice in the event that Deutsche Börse AG – despite a prior notice of default – commits a breach of material duties arising from this Agreement.

(4) Notice of termination shall be by way of written declaration to the other contracting party.

§ 6 Final provisions

(1) This Agreement may be unilaterally changed by Deutsche Börse AG, conditional upon the ATP member being given at least 6 weeks notice of the changes in written form. Such

ATP Agreement
for participation in the "Automated Trading Program" (ATP) via the electronic trading system Xetra®

DEUTSCHE BÖRSE

unilateral changes shall entitle the ATP member to terminate the Agreement, effective at the time the unilateral changes take effect. In the event, the ATP member has not objected in writing to Deutsche Börse AG, the ATP member shall be deemed to have accepted the change. In case of objection, Deutsche Börse AG is entitled to terminate this Agreement with effect at the time the unilateral changes take effect. Any termination requires the written form.

(2) This Agreement is governed by the laws of the Federal Republic of Germany. Place of jurisdiction for both contracting parties in the event of disputes arising from this Agreement shall be Frankfurt am Main.

(3) In the event that any individual provision of this Agreement should be or become invalid or impracticable, this shall not affect the validity of the other provisions hereof. Any invalid contractual provision shall be replaced either by the statutory rule or (in the event of absence of such a rule) such provision as the parties would have admissibly adopted in good faith if they had been aware of the invalidity or nullity of the term that it replaces. The same shall apply insofar as it shall be determined that the contractual regulations are incomplete.

(4) This Agreement constitutes the entire agreement and supersedes all prior agreements and understandings with respect to the subject matter hereof. The parties agree that any mutual claims resulting from any prior agreement are herewith deemed to be discharged by the execution of this agreement.

Place and date

For the ATP member | For the ATP members compliance department

(Company stamp and authorized signatures including names in block letters)

For Deutsche Börse AG

Appendix B

List of Abbreviations

List of Abbreviations

AA .... Algorithmic Agency

AT .... Algorithmic Trading

CATS .... Computer Aided Trading System

DB .... Deutsche Boerse

ECN .... Electronic Communications Network

FIX .... Financial Information eXchange

LSE .... London Stock Exchange

MCap .... Market Capitalization

NYSE .... New York Stock Exchange

OMS .... Order Management System

PT/SA .... Proprietary Trading and Statistical Arbitrage

VAR .... Vector Autoregression

VMA .... Vector Moving Average

XBRL .... eXtensible Business Reporting Language

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07/2003 - 04/2005	Trading Room Manager, Carleton University, Canada
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Karlsruhe, 30.06.2009