Order-Channel Management in Institutional Equity Trading:

A Framework for IT-Driven Trading Innovations

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Papers of the Cummulative Dissertation

Paper 1

B. Ende, P. Gomber and A. Wranik
An Order-Channel Management Framework for Institutional Investors
In: *International Conference on Wirtschaftsinformatik Proceedings (WI2007), Vol. 2, pp. 705–722, Karlsruhe, Germany, 2007*

Paper 2

B. Ende
IT-Driven Execution Opportunities in Securities Trading: Insights into the Innovation Adoption of Institutional Investors
In: *European Conference on Information Systems Proceedings (ECIS2010), Paper 88, Pretoria, South Africa, 2010*

Paper 3

B. Ende, P. Gomber, M. Lutat and M.C. Weber
A Methodology to Assess the Benefits of Smart Order Routing
In: *Software Services for e-World, IEEE (IFIP) Advances in Information and Communication Technology, 341(1), pp. 81–92; Springer, Boston, USA, 2010*

Paper 4

B. Ende, T. Uhle and M.C. Weber
The Impact of a Millisecond: Measuring Latency Effects in Securities Trading
In: *International Conference on Wirtschaftsinformatik Proceedings (WI2011), Paper 116, OUTSTANDING PAPER AWARD NOMINEE, Zurich, Switzerland, 2011*

Paper 5

B. Ende and J. Muntermann
Assessing IT-Supported Securities Trading: A Benchmarking Model and Empirical Analysis
In: *Americas Conference on Information Systems Proceedings (AMCIS2010), Paper 476, BEST PAPER AWARD NOMINEE, Lima, Peru, 2010*

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Abbreviations

ADV	Average Daily Volume
AP	Arrival Price
ATS	Alternative Trading Systems
AuM	Assets under Management
AVE	Average Variance Extracted
bps	Basis Points
CCP	Central Counter Party
cf.	confer (compare with)
CIO	Chief Investment Officer
CR	Composite Reliability
CSA	Commission Sharing Agreement
CSD	Central Securities Depository
DAX	German Large Share Index
DMA	Direct Market Access
ECN	Electronic Communication Network
ESMA	European Securities and Markets Authority
e.g.	exempli gratia (for example)
et al.	et alia (and others)
EU	European Union
FCA	Financial Conduct Authority
FIX	Financial Information eXchange
HFT	High-Frequency Trader
ICSD	International Central Securities Depository
i.e.	id est (that is)
IOI	Indication of Interest
IP	Internet Protocol
IS	Information System
ISIN	International Securities Identification Number
IT	Information Technology
MiFID	Markets in Financial Instrument Directive
MTF	Multilateral Trading Facility
NASDAQ	National Association of Securities Dealers Automated Quotations
NDOH	Non-Delegated Order Handling
NYSE	New York Stock Exchange
OCM	Order-Channel Management
OMS	Order Management System
OTC	Over-The-Counter
NSC	Nouveau System de Cotation
PLS	Partial Least Squares
PI	Price Improvement
P2P	Peer-to-Peer

RegNMS	Regulation National Market System
RQ	Research Question
SEC	Securities and Exchange Commission
SEM	Structured Equation Model
SETS	Stock Exchange Electronic Trading Service
SOR	Smart Order Router
SWIFT	Society for Worldwide Interbank Financial Telecommunication
TAM	Technology Acceptance Model
TPB	Theory of Planned Behavior
TRA	Theory of Reasoned Action
TT	Trade-Through
TTF	Task-Technology Fit
UK	United Kingdom
US	United States
USA	United States of America
VDAX	DAX Volatility Index
VWAP	Volume Weighted Average Price
XETRA	eXchange Electronic TRAding
XLM	eXchange Liquidity Measure

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Introductory Paper

Order-Channel Management in Institutional Equity Trading: A Framework for IT-Driven Trading Innovations

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Bartholomäus Ende

Abstract

IT-driven trading innovations offer institutional investors alternative trading channels to broker delegated order handling. Motivated by the impact on intermediation relationships in securities trading and the adoption rate of such trading channels, the new option of self-directed order handling is analyzed. To capture the prerequisites for institutional investors to insource their order handling, an order-channel management (OCM) framework is introduced. It is based on a structural approach to account for the increasing complexity in comparison to traditional intermediary services. Drivers for the adoption of an OCM framework are investigated from the strategic perspective. Operational OCM is based on the business value of IT analysis of distinct trading innovations. It includes smart order router technology, low latency technology as an upgrade for existing IT-driven trading channels as well as negotiation dark pools, representing alternative trading venues. Evidence that all investigated IT-driven trading innovations generate additional business value is provided as one result. However, it is also shown that they exhibit entry barriers tightly related to investor size. Further, Task-Technology Fit is proven to be the major driver for the adoption decision. Consequently, IT-driven trading innovations should increase trading control, satisfy high anonymity and varying urgency demands.

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1 Preface

1.1 Research Motivation and Objectives of the Thesis

The role of human intermediation has a long tradition in securities trading (Venkataraman 2001; O'Hara 2004). Historically, it was induced by the limited number of exchange memberships restricting direct interaction at trading floors. Thus, delegation to brokers has been the traditional trading channel for most investors. Brokers act on behalf of their customers as intermediaries (Schwartz and Francioni 2004). This leads to an outsourced order handling of institutional investors[1].

The above division of labor became even eponymous for key players in securities trading: As intermediaries sell securities trading services such as access to exchanges and identification of suitable counterparties, they are referred to as sell-side. Conversely, investors, consuming this kind of trading services, belong to the buy-side (Harris 2003).

The implementation of institutional investment strategies relies on executing large orders (block orders) in a cost-efficient way (Kissell et al. 2003). However, block orders exhibit disproportional transaction costs (Almgren et al. 2005). Moreover, the growth of (European) assets under management (AuM) exhibits a long-term upward trend (EFAMA 2004). As individual AuMs of large institutional investors grow above-average (ICI 2014), the implementation of their strategies becomes particularly challenging. Increasing trading volumes (Bloomberg 2015) even aggravated this situation as they stress the limits of manual, intermediated order handling by humans.

In the early 1970s, information technology (IT) relieved securities trading from the constraints of human appreciation by paving the way for the computerization of exchanges (Schwartz and Francioni 2004). The automation of trading comes as no surprise; it just reflects the implications of Solow (1957), who considers technological innovation as the major driver of economic growth. But in case of securities trading, IT does not only lead to immediate productivity improvements such as increased straight-through processing rates (Weitzel et al. 2003), but also introduces new, alternative *IT-driven trading channels*. In this regard an IT-driven trading channel subsumes one or more necessary *IT-driven trading innovations*[2], chosen for an order, which enable buy-side traders to search for counterparties.

The central pillar of these new channels is *direct market access* (DMA). This innovation breaks the restrictions of direct trade interaction to exchange members only. Instead, brokers can now virtualize their previously exclusive market access and grant other investors direct access to security markets via their technical infrastructure. DMA omits additional sell-side trading services and thus represents a

[1]Unlike retail investors, institutional investors are defined as non-bank organizations such as insurance companies, pension, mutual or hedge funds with high assets under management (Vittas 1998).

[2] For simplicity the terms channel and innovation are used throughout this thesis as an abbreviation for IT-driven trading channel and IT-driven trading innovation, if not stated otherwise.

non-intermediated tool for institutional investors at considerably lower costs (Domowitz and Yegerman 2005). Thereby, this innovation allows the buy-side to take over control of their trading. The most simple form of a new channel for institutional investors is to employ own human buy-side traders, who use pure DMA. In doing so, conducting even this simple type of self-directed trading already allows the buy-side to insource their order handling, instead of delegating it to external sell-side traders.

Based on DMA, further cost-efficient but more automated channels arose from complementary innovations such as *algorithmic trading* and *smart order routing*. While the first simulates the order handling of a human trader at one single electronic exchange only, the latter does the same across multiple markets. On top, the computerization of exchanges has enabled the emergence of *alternative trading venues* such as *dark pools*, which employ innovative market mechanisms, implemented by proprietary software and off-the-shelf hardware. This kind of innovation creates a new way for block orders to find suitable counterparties.

Figure 1 illustrates the traditional delegated order handling (upper part) and the new option for a *self-directed and thus more disintermediated order handling* via technology adoption (lower part). This option leads to the question whether – and, if so, how – self-directed order handling provides value for the implementation of institutional investment strategies, i.e. whether it has the potential to reduce transaction costs for executing large orders.

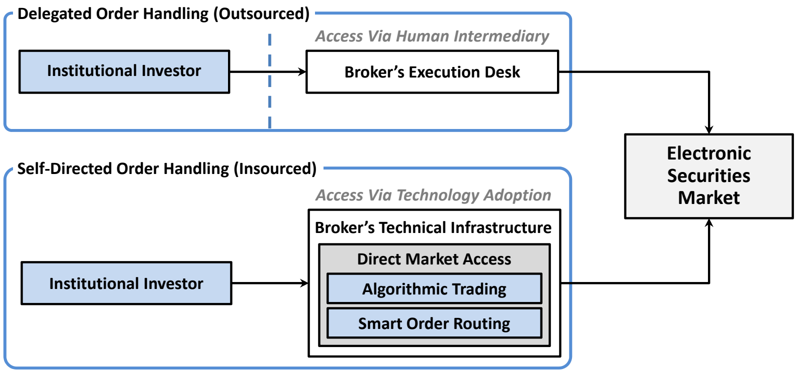

Figure 1: Delegated vs. Self-Directed Order Handling

In the past, IT-based innovations have proven to cause relevant changes in workflows of many modern industries (Brynjolfsson and Hitt 2000). Nevertheless, the self-directed use of new channels (*order-channel management*) is largely uninvestigated. Since a considerable part of institutional investors already adopted such channels (EdHec 2005; Financial Insights 2005, 2006), the thesis at hand picks up on this new opportunity set for institutional investors. In doing so, it shows how a higher IT-sophistication of the buy-side can increase control over the implementation of their investment decisions.

For buy-side trading desks; the switch from broker delegated order handling to an in-house order-channel management (OCM) implies greater complexity. To successfully handle this complexity two basic layers exist: The first tackles strategic decisions such as the adoption of new channels. Beyond, strategic OCM is centered on the setup of an in-house order handling. In this context, the Productivity Paradox by Brynjolfsson (1993), which states that IT investments do not directly turn into productivity increases, should be borne in mind. Accordingly, institutional investors require knowledge concerning the business value provided by innovations for the characteristics of their order flow. This leads directly to the second operational OCM layer, which deals with issues regarding daily order handling via preselected channels. Together, these two layers set the structure of the thesis.

Motivation of Order-Channel Management

Since the end of the last century, new channels provide institutional investors with the opportunity to reconsider their intermediation relationship to brokers. Nevertheless, this aspect is still not covered by literature. Recent research on market microstructure is centered on market mechanisms and their effect on trading outcomes (O'Hara 1995; Madhavan 2000; Hasbrouck 2007). The vast majority of this extant literature focuses on prices, trading volumes, transaction costs as well as trading behavior. For the buy-side, implicit trading costs are of particular importance. The reason behind is, that implicit trading costs are not only hard to forecast, but also represent the main part of institutional trading costs (Keim and Madhavan 1998). As implicit trading costs prevent many institutional investors from beating their target benchmarks (Kissell et al. 2003), academia investigates their major components such as market impact[3] (Lillo et al. 2003; Almgren et al. 2005; Bikker et al. 2007). Based on resulting transaction cost models, researchers like Almgren and Chriss (2000) or Kissell et al. (2003) analyze how an optimal order execution could be achieved. This provides the theoretical basis for designing innovations like trading algorithms. Most recent literature on market microstructure focuses on the isolated effects of these innovations. Among them are algorithmic trading (Gsell 2008; Hendershott and Riordan 2009; Hendershott et al. 2011), high-frequency trading (Brogaard 2010; Cvitanic and Kirilenko 2010; Jovanovic and Menkveld 2011; Zhang and Riordan 2011; Hasbrouck and Saar 2012; Haferkorn et al. 2013) and dark pools (Hendershott and Mendelson 2000; Gresse 2006; Næs and Ødegaard 2006; Ready 2010).

In summary, academic literature is primarily centered on the isolated effects of individual innovations; the only exception being Yang and Jiu (2006), who refer to orders suitable for algorithmic trading and suggest a quantitative framework to select an appropriate algorithm. Their framework is based on historical performance attributions along order and market condition related factors, which are used to forecast future performance. Although Wagner (2006) provides operational guidance on the use of certain trading channels, there is still a lack of research dealing with both the strategic and operational decisions by institutional investors and the employment of

[3] An evaluation of additional implicit trading cost components such as delay and opportunity costs, price appreciation and timing risk is provided by Kissell et al. (2003).

a suitable bundle of channels. Thus, the first research question (RQ) and starting point for this thesis formulates as follows:

RQ1: *How to structure a systematic approach describing the usage of IT-driven trading channels for institutional investors?*

To further deepen this discussion, the thesis refers to two subsequent and more specific RQs. The scope ranges from the strategic OCM decision, on whether to employ certain channels to an operational OCM question regarding particular innovations and their business value.

Strategic Order-Channel Management

Innovations such as algorithmic trading originate from the US. These tools have initially been developed by brokers to facilitate their business and to increase their cost efficiency by automation. Accordingly, in the US such innovations account for 50% to 70% of overall order flow (Carpenter 2013; Treleaven et al. 2013). In Europe, the numbers are lower. Estimates of European institutional investors' order flow being processed via automated trading range between 24% and 43% (ESMA 2014a; Grant 2011).

While the relevance of such innovations for the overall market is indisputable, many institutional investors are still undecided whether or not to adopt an OCM framework. According to descriptive studies like EdHec (2005), Financial Insights (2005, 2006) or Gomber et al. (2009) the acceptance rate of self-directed in-house trading by the means of technology adoption ranges between 50% and 60% among large investors. This might be due to the fact that for institutional investors technologies for automating their trading are relatively new, while brokerage firms have long-term experience with these tools. Further, adopting trading technologies does not necessarily lead to value-creation. Instead, an institutional investor has to set up all resources to insource the trading process (Ende et al. 2007). Thus, only large investors with sufficient economies of scale are able to take advantage of such innovations (Gomber et al. 2009).

Essentially, the adoption decision of process owners who are responsible for organizing the order handling at institutional investors, has not been analyzed yet. Nevertheless, in the light of the potential, which IT has to change workflows (Brynjolfsson and Hitt 2000) and the impact on the buy-side's intermediation relation, the identification of involved drivers as well as their interaction are of interest for all parties. In Information System (IS) research, a rich body of literature deals with such drivers of technology adoption (Venkatesh et al. 2003; Jeyaraj et al. 2006). Thereof, the Technology Acceptance Model (TAM) by Davis (1989) has gained most importance. TAM has already been successfully applied across a multitude of domains (Venkatesh et al. 2003). Nevertheless, only few authors investigate the domain of securities trading in this respect. Other than for retail investors, where Lai and Li (2005) apply TAM to investigate the adoption of online banking. The adoption decision of brokers is analyzed from two perspectives: The adoption of workstations is explained by Lucas and Spitler (2000) via TAM. Khalifa and Davison (2006), on the other hand, show the relevance of coercive, mimetic as well as normative pressures for the introduction of electronic trading systems.

As IS literature has not covered the technology adoption at institutional investors in relation to the decision-making of process owners yet, the following second RQ is stated as:

RQ2: *Which factors drive or inhibit process owners from setting up an order-channel management framework?*

Operational Order-Channel Management

Once process owners decide to adopt an OCM framework, a scheme, which allocates individual orders to a suitable channel, becomes necessary (Wagner 2006). That way, capabilities of these channels are matched against characteristics of each individual order (Yang and Jiu 2006). This operational knowledge, how process owners can evaluate the business value of trading channels, is also closely related to their decision-making within strategic OCM. Accordingly, experiences gained in daily operations within operational OCM constitutes a valuable input for subsequent, strategic decisions. The aforementioned evaluation of the business value of potential innovations for a given type of order flow relies inherently on suitable performance metrics (Hitt and Brynjolfsson 1996). In this field, IS research provides a huge body of literature; be it for the analysis of the business value of IT (Kauffman and Weill 1989; Mukhopadhyay et al. 1995; Kohli and Devaraj 2003; Melville et al. 2004) or process performance (Subramanyam and Krishnan 2001; Lee 2004). So far, innovations have attracted different levels of academic attention with respect to the analysis of their business value. Particular interest is dedicated to algorithmic trading. For instance, Domowitz and Yegerman (2005) highlight that trading algorithms allow overall cost savings compared to human traders. They also outline for which types of orders this innovation is most applicable. Later, Domowitz and Yegerman (2011) take a perspective more focused on end users and concentrated on the usage patterns of algorithms and their costs. In this regard, Gsell and Gomber (2009) analyze similarities and differences among human and algorithmic traders.

Nevertheless, suitable metrics for the evaluation of the business value of IT-driven trading innovations have not been provided for all stages along the securities trading value chain so far. Thus, the third and last RQ is posed as:

RQ3: *Which performance metrics enable process owners to assess the advantages of particular IT-driven trading innovations?*

1.2 Structure of the Thesis

To answer the aforementioned research questions, this cumulative dissertation is made up of five papers: The first RQ on how to structure a systematic approach for the usage of IT-driven trading channels is addressed in **Paper 1**. This paper provides the theoretical foundation for the thesis via an in-depth literature review and industry screening. Based on this, the general OCM framework is introduced and backed by expert interviews.

The second RQ concerning factors, which either drive or inhibit the process owners' strategic decision-making regarding the introduction of an OCM framework, implies classic technology adoption research. Therefore, a quantitative survey is conducted. It is based on a causal explanation model analyzed in **Paper 2**.

The third and more operational RQ assessing the advantageousness of particular innovations relates to business value of IT analysis. In case of securities trading, a wide range of innovations exists, which can be employed at different stages along the securities trading value chain. The starting point is the software used at a trading desk. There a variety of trading channels to communicate orders to execution venues exists, which include options for faster connection layouts at additional costs. Finally, a securities market might introduce innovations itself. Due to this diversity, it is hardly possible to provide a holistic metric for the business value of innovations. For that reason, three different innovations have been chosen. For each of them, a measurement methodology is proposed in theory and then analyzed empirically (**Papers 3 to 5**). The empirical tests are based on order book and trading data. For the evaluation of smart order router technology (**Paper 3**) an optimal order router is simulated. This simulation includes a transaction costs modeler to deduct additional costs for switching trading venues. To test statistical significance of potential savings, real order executions are passed through this simulation. **Paper 4** assesses low latency technology. The simulation employed for this purpose is based on the concept of order book fluctuations. That way, the effects of latency on the trustworthiness of available limit prices and volumes is investigated. Finally, in **Paper 5** a benchmarking model is introduced to evaluate negotiation dark pools, which lack a transparent price indication. It resorts to best quotations available at traditional exchanges and conceptualizes how executions at such alternative trading venues can be compared

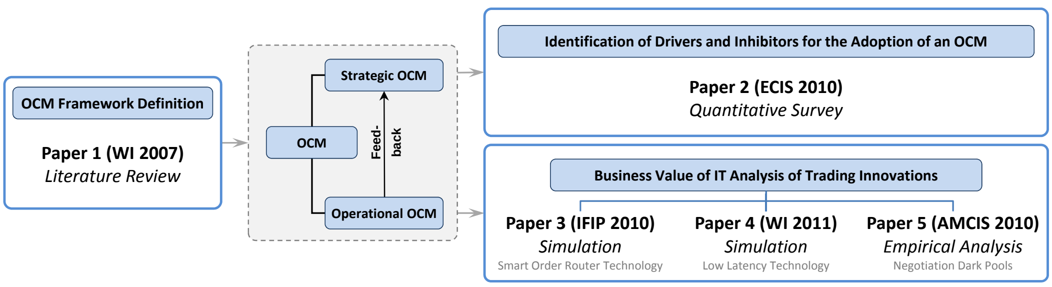

Figure 2: Structure of the Thesis on Order-Channel Management

to these quotations. The benchmarking model is then applied by empirical analysis of an exemplary negotiation dark pool.

Figure 2 provides an overview of the methods employed in the different papers and the overall structure of the thesis.

The remainder of this introductory paper is structured as follows: At first, the research context is briefly introduced within the next subsection. Here, changes of the buy-side's intermediation relationship to the sell-side, induced by automation and technology adoption, are depicted. This provides the starting point for the development of the OCM framework. In section 3 the employed research methods are described. The main results of the five papers are then summarized in section 4. Contributions to literature as well as practical implications are discussed in section 5. Finally, a conclusion is provided in section 6. It includes a discussion of limitations and provides an outlook on potential future research in this field.

2 Research Context: How IT-Driven Trading Channels Change the Buy-Side's Intermediation Relationship

At the beginning of this century, institutional investors were given an alternative to the traditional intermediation by brokers. Whilst this opportunity is attributable to new channels, many factors have to be considered when dealing with the organizational structure of institutional order handling might it be traditionally delegated or self-directed by the means of IT adoption. Figure 3 depicts four factors, whose examination constitutes the three subsections of the research context: The starting point is the available trading *infrastructure*. Based on this, ongoing *technology development* reduces media breaks and fosters automation in securities trading. A *competitive environment* for the buy-side or the sell-side impacts adoption rates and fuels innovations. Finally, *regulation* provides the overall *framework*.

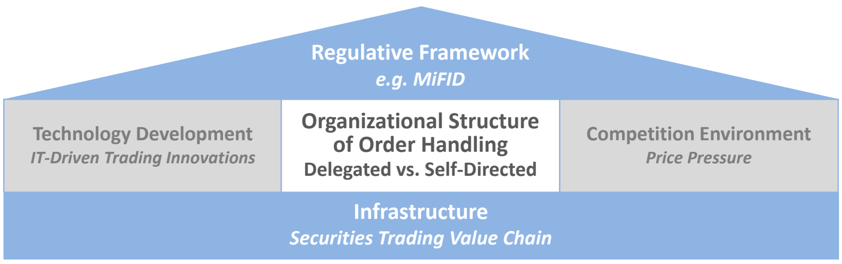

Figure 3: Influences on the Organizational Structure of Institutional Order Handling

2.1 Traditionally Delegated Order Handling

Until the end of the 1990s, the order handling of institutional investors was completely delegated to market intermediaries. In these days, buy-side trading desks had primarily been concerned with the selection and supervision of brokers[4] to whom incoming orders were sent. Some trading desks also decided, whether brokers should act as agents or unwind the order for a fixed price (principle bid). The reason behind this delegated way of institutional order handling was the existing infrastructural reality, represented in the tripartite structure (Harris 2003) of the *securities trading value chain* (cf. figure 4).

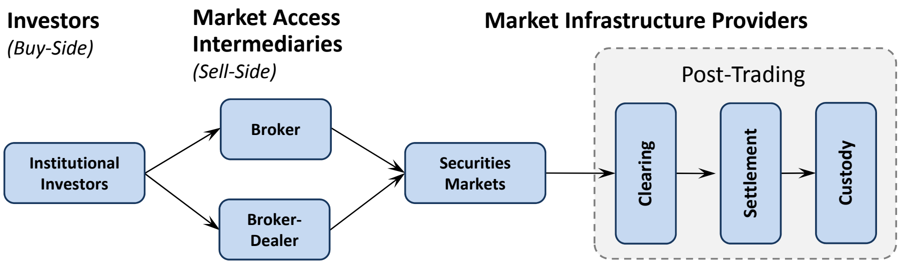

Figure 4: Securities Trading Value Chain

The key feature of the securities trading value chain is intermediation. Instead of direct interaction of investors at security markets, brokers control access to regulated trading venues or negotiate trades over-the-counter (OTC). This allows economies of scale and scope (Schwartz and Francioni 2004). In this regard, the buy-side profits not only from the market knowledge due to the specialization of brokers, but also benefits from the positive network externality generated by broker-contacts to other clients. That way, brokers open access to these investors' latent trade interests (Harris 2003). Moreover, intermediated market access is a cost-efficient way to safeguard smooth post-trading operations. Rather than each investor having to verify the ability of its counterparties to unwind trade obligations, brokers assure this post-trading requirement for themselves and their clients only. For traditional floor-based exchanges, obviously the number of market participants able to trade in a non-intermediated way is limited by the capacity of trading floors. Further, floor traders employ sophisticated rules and communication protocols. Even investors, who can afford an exchange membership, have to proof that they master these by passing trader examinations; a burden brokers ease on their clients. Bearing this in mind, institutional investors benefit in a number of ways from intermediary services offered by brokers.

Beyond this classic market access intermediation, attempts to trade at foreign exchanges might introduce the necessity of additional intermediaries. In cases of a fragmented post-trading landscape such as in Europe (Schaper 2008), International Central Securities Depositories might be required to grant access to a foreign post-trading infrastructure. This intermediation and the costs involved constitute an important aspect within the analysis of the potential of smart order router technology in **Paper 3**.

[4]Like in figure 4 a distinction is made between brokers and broker-dealers: While the former act as agents for their clients only, the latter also trade on their own account (proprietary trading) (Harris 2003). For simplicity the term broker is used throughout this thesis wherever possible.

2.2 A Critical Reflection of Delegated Order Handling

While delegating order handling eases the work of buy-side trading desks, the intermediation relationship involved represents *"[t]he most important principle-agent problem in [market] microstructure"* (Harris 2003, p. 8).

In this regard, the buy-side is primarily worried about *information asymmetries* with respect to brokers' efforts to provide best execution. Accordingly, the buy-side is generally interested in self-directed trading instead of broker delegation. Concerns resort from the multidimensional nature behind the concept of execution quality. This multidimensionality requires complex verification procedures (Macey and O'Hara 1997) and lets the monitoring of broker executions become complicated. Besides trade prices, appropriate measures have to incorporate different dimensions of order complexity such as execution urgency or size (Kissell et al. 2003). In particular this is required for orders of institutional investors, which force brokers to seek counterparties across multiple trading channels (Wagner and Edwards 1993). According to Akerlof's (1970) argumentation, the level of execution quality buy-side trading desks might expect from their brokers is limited by its verifiability and discriminability[5].

A direct consequence of these information asymmetries are concerns by institutional investors that brokers might take advantage from the private information contained in their clients' order flow (Schwartz and Francioni 2004). One example of such illegal practice is *front running* that describes a process during which brokers exploit their clients by trading ahead of them. That way, front running profits from the effect known as *order exposure problem* (Harris 2003): Markets expect block orders to originate from informed investors. Accordingly, they react with unfavorable price movements (market impact) once such orders have been revealed. Additional market impact results from the imbalance of supply and demand induced by the order execution itself. Due to the zero-sum nature of trading (O'Hara 1995), market impact is aggravated by brokers who front run orders from their clients. Initially, such brokers trade on the same side as their clients and thus increase imbalance of supply and demand. Later, these brokers closes their position at prices favorable to them but less to their clients.

To protect investors from the above information asymmetries, market regulators have introduced best execution requirements applicable to brokerage firms[6]. Within the European Union (EU) e.g. these rules form one central pillar of the Market in Financial Directive (MiFID). With the goal of harmonizing regulation among European financial markets MiFID had to be applied from November 2007 (MiFID 2007). Regarding best execution this directive follows a process-based approach by obliging investment firms to establish and disclose *best execution policies*. However,

[5]Improvements of execution quality beyond a verifiable level become indistinguishable from executions, which just reach this measurement limit. Accordingly, efforts of brokers to provide superior executions will not be appropriately compensated and thus pushed out of the market (Harris 2003).

[6]These regulations are not limited to brokerage firms only, but address investment firms in general.

given the example of Germany, Gomber et al. (2012) show in order to fulfill these obligations, brokers implement minimal standards only.

For brokers, common practices for trying to retain or attract new buy-side order flow are *soft commission agreements* or *bundled trading*. With regard to the organizational structure of order-handling Steil and Perfumo (2003) illustrate how these agreements can prevent institutional investors from adopting new channels. The basis of soft commissions are certain services and goods like research and infrastructure provided by a broker free of charge. In return, the receiving institutional investor grants a certain amount of its order flow to the broker. That way, payments for adjacent broker services are bundled with brokerage commissions for the executed order flow (Schwartz and Francioni 2004). As a consequence, parts of the institutional investor's order flow cannot be executed via self-directed and potentially more cost efficient execution channels.

Historically, soft commission agreements became popular before 1^{st} of May, 1975 in the US, when brokerage commissions were regulated (Harris 2003) and well before new channels for self-directed order handling emerged. For brokers this practice provides an opportunity to distinguish themselves from competitors and to a certain extend highlight the quality of their brokerage services via good research. However, soft commission agreements also create a second principle-agent problem, which is based a level higher in the securities trading value chain: For institutional investors these agreements induce a conflict of interest based on the chance to save expenses from their own resources at the cost of higher brokerage commissions paid directly from their clients' deposits (Schwartz and Steil 2002). Accordingly, buy-side companies such as mutual funds take in this example the role of agents and fund holders that of principals. Additionally negative impacts of soft commissions on trading costs are highlighted by Johnsen (1994). Together with other researchers such as Livingston and O'Neal (1996) and Conrad et al. (2001) they outline the danger of trading cost manipulations due to a lack of transparency and the incorporated impediment for best execution.

Due to the negative effects of bundled trading on best execution, the practice of soft commissions has been monitored by regulators. At first the UK Financial Conduct Authority (FCA) obliged the buy-side to obey a clearer separation between research and execution payments (FCA 2013) in 2006. In this course the FCA limited the range of services, which buy-side mangers are allowed to consume in exchange of broker commissions and put forward the concept of commission sharing agreements (CSAs)[7]. CSAs are based on a properly negotiated split of commissions between executing brokers and one or multiple independent research providers. That way, the transparency of execution costs and those of additional services such as research is strengthened. Nevertheless, payments via CSAs still require buy-side trading desks

[7] An in-depth discussion on this topic is provided by Euro IRP and Investorside in their guide to Commission Sharing Arrangements in the UK and Client Commission Arrangements in the US, which is accessible under www.euroirp.com/cms/documents/CSA_CCA_Final.pdf.

to reserve parts of their order flow to be delegated to brokers. Accordingly, economies of scale for new channels are reduced, which might restrain the usage of self-directed order handling. Bearing this in mind, the effects of soft commissions and bundled trading on the adoption decision of process owners concerning new channels is analyzed in **Paper 2**. At least until 2017 these trading agreements will impact self-directed trading; by that time it is expected that MiFID II comes into force. In the light of the new directive a complete unbundling of research payments from order executions has been suggested by the European Securities and Markets Authority (ESMA). For that purpose, the final ESMA report on MiFID II proposes research payments either to resort from own resources of an investment firm or from a separate research account, which is explicitly charged to clients (ESMA 2014b).

2.3 Emergence and Implications of Self-Directed Order Handling

For self-directed order handling IT-driven trading capabilities play a crucial role. The reason behind is not only that *"[security] markets are essentially information-processing mechanisms"* (Harris 2003, p. 8), but also IT is a general-purpose technology and as such enables complementary innovations (Bresnahan and Trajtenberg 1995). For buy-side trading desks such complementary innovations are new channels providing the foundation for self-directed order handling. That way recent IT developments in combination with steadily falling prices initiated a transformation of securities trading similar to changes other industries have undergone before (Huff and Munro 1985).

In the 1970s the basis of this transformation has been established by the electrification of exchanges (Schwartz and Francioni 2004). Nevertheless, the automation of major security markets did not take place until the 1990s. At that time the proliferation of electronic central limit order books (e-CLOB)[8] was initiated (Engelen et al. 2006). These systems increase cost-effectiveness by automating order matching and price discovery, which strengthens operational fairness. On the one hand e-CLOBs enforce strict price-time priority (Harris 2003), on the other they display available but unexecuted orders to all market participants. By increasing transparency e-CLOBs not only reduce information asymmetries but also improve liquidity[9] and information processing (Pagano and Röell 1996; Jain 2005). However, it took until the end of the last century when complementary innovations propagated up the securities trading value chain and enabled self-directed order handling.

Beforehand the sell-side profited in several ways from automated security markets. First and foremost, it was given direct market access, so that brokers could electronically communicate orders to exchanges. This allows sell-side trading services to be provided more efficient. Because electronic exchanges do not require physical presence

[8] An in-depth discussion of e-CLOBs is provided by Schwartz and Francioni (2004).

[9] Liquidity describes the ability of a security to be bought and sold in large volumes with low or ideally no negative price movements at all (O'Hara 1995). For an in depth discussion of the concept liquidity along its three dimensions depth, breadth and resiliency the reader might refer to Brunner (1996), Sarr and Lybek (2002) or Amihud et al. (2005).

at trading floors media breaks such as phone calls to floor traders were eliminated. Standardized communication interfaces between electronic exchanges were introduced, which enabled the complementary innovation of trading algorithms. The first incarnations were developed at Morgan Stanley approximately in 1980 for the purpose of pairs-trading and statistical arbitrage (Leshik and Cralle 2011). The purpose of trading algorithms up to now is to alleviate the work of a trader by automating the slicing of a large order and timing the dissemination of created sub-orders to a market. That way, algorithms are more cost effective than their human counterparts; nonetheless, they are still restricted to rather simple order sizes (Domowitz and Yegerman 2005). Before the end of the last century, the US sell-side invested in its IT-based trading capabilities to reduce costs (Goldstein et al. 2009) and thereby fuelled innovations. The reason behind were regulatory changes such as the introduction of Order Handling Rules in 1997 by the Securities and Exchange Commission (SEC) or Decimalization, which was enforced in 2001 (Harris 2003). Both lead to shrinking profit margins and required the sell-side to strive for efficiency gains. Order Handling Rules strengthen competition by cost effective electronic communication networks (ECNs)[10], which are based on e-CLOBs (Barclay et al. 2003; Fink et al. 2006). Decimalization reduced the minimum price variation (tick sizes) from one-sixteenth dollar fractions to one cent[11]. Consequently bid/ask spreads became narrower (Bessembinder 2003), which in return decreased profitability of dealer strategies such as market-making[12] substantially. Brokers, who directed orders to other executing firms such as market-makers and received financial incentives in return, were also hit financially, as these payments for order flow were decreased (Harris 2003). Additionally competitive pressure derived from the market downturn after the dot-com bubble burst. To overcome the above decrease of profit margins the sell-side had to change its revenue model. One option to achieve that was the provision of automated, low touch services with the potential of high turnovers (Goldstein et al. 2009). As such discount brokerage services require high straight-through processing rates, the sell-side has established a sophisticated electronic and algorithmic trading infrastructure for their clients (Khanna 2007).

Simultaneously, the commitment to streamline trading cost increased at the buy-side. This development was driven by regulatory actions as well as competitive pressure. In 2002 the SEC imposed sanctions on buy-side institutions, which failed to fulfill their best execution obligations introduced by the Advisers Act (SEC 2013). These regulatory actions increased the buy-side's focus on order-handling and trading costs. Additionally competitive pressure resorted from the decline of AuMs and management fees during the sharp market downturn between 2000 and 2003. Later,

[10]A detailed discussion of ECNs is provided by McAndrews and Stefanadis (2000).

[11]The New York Stock Exchange already reduced for most of its stocks their minimum tick size from one-eighth dollar fractions to one-sixteenth in June, 1997 (Jones and Lipson 2001).

[12]Market-makers enable trading of other market participants by providing both buy and sell quotations. In exchange, they earn the bid-ask spread. The Tabb Group estimates losses from Decimalization to 27b$ in their 2004 report on Institutional Equity Trading in America – A Buy-Side Perspective.

increasing market shares of passive, low-cost investment products such as exchange-traded funds maintained this competitive pressure on established active buy-side mangers (Lan et al. 2013). Moreover, empirical evidence is provided by studies like Jones and Lipson (2001) and Bollen and Busse (2006) that institutional trading costs increased after tick size reductions in the course of Decimalization. Accordingly, cost advantages of new algorithmic trading capabilities allowed technology-minded buy-side traders to react. In doing so, high volume buy-side traders such as hedge funds played a leading role concerning the first step towards self-directed order handling (Khanna 2007). At the beginning, the decision set of their trading desks was merely extended by the option to actively select algorithmic execution strategies provided by brokers. But very soon the buy-side became dissatisfied with the execution quality and flexibility offered by the sell-side (Institutional Investor 2002). To overcome limited trading control, institutional investors started to seek for broker-neutral ways to employ trading algorithms (Opiela 2005; Irrera 2013).

The technical backbone for broker-neutral trading algorithms is the processing of buy-side orders, starting with the entrance into a buy-side order management system up to their execution at an electronic securities market, without any media breaks (Khanna 2007). Such a straight-through processing requires standardized interfaces for the electronic disintermediation of order instructions, which gave the Financial Information eXchange (FIX) protocol the chance to evolve a de facto standard within securities trading (Aldridge 2010). With the proliferation of FIX, DMA became available to buy-side trading desks during the millennium. DMA considerably reduced buy-side interaction with the sell-side. By employing DMA services institutional investors merely use broker infrastructure to gain access to security markets. Accordingly DMA is nowadays a synonym for disintermediated remote access to electronic order books, which facilitates self-directed order handling. That way DMA might provide buy-side trading desks with positive effects comparable to those Easley et al. (2014) highlighted in their study on a technology upgrade at the New York Stock Exchange in 1980. This upgrade has not only established an equal playing field among off- and on-floor traders with respect to their responsiveness, but has also led to positive effects on overall market quality parameters.

In order to take advantage of self-directed order handling buy-side trading desks had to increase their IT investments (Groenfeldt 2014). These expenses paid off for a large part of institutional investors, who familiarized themselves with DMA and started to use algorithms provided by independent software providers or even engaged in self-developed algorithmic solutions. Some of these early adopters reported trading cost savings of 27% (Institutional Investor 2002). Such savings most times resulted from buy-side traders being unburdened from the timeconsuming part of their work by the usage of algorithms. This opened the opportunity to focus on high-touch orders, whose diligent handling gives potential to add value. On top of that self-directed order handling enables closer interaction between portfolio management and traders as both reside with the same institution. Consequently, buy-side traders can gain deeper insight into the reasoning for certain trades (Opiela 2005). Evidence by Anand et al. (2012) arguments in favor of the buy-side's investments in innovations. Their research highlights that trading desk performance is not only sustainable but also an important contributor to an institutional investor's overall success.

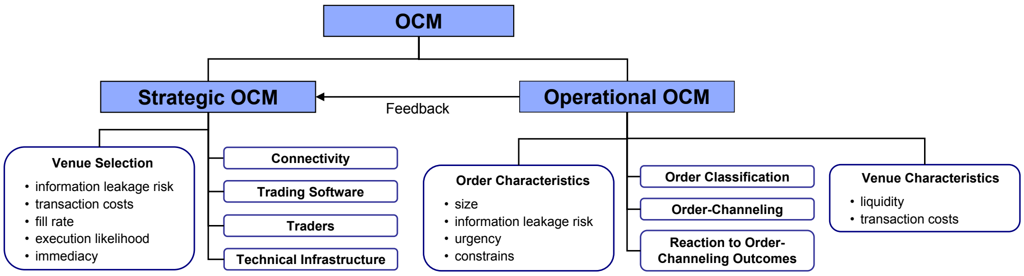

Figure 5: Order-Channel Management Responsibilities from Ende et al. (2007)

The adoption decision for self-directed order handling comes along with new responsibilities for the OCM of a buy-side trading desk. An overview of general factors to account for as well as their exemplary decomposition on the strategic and operational layer is provided in figure 5.

With the emergence of ECNs in the US one additional responsibility for buy-side trading desks became the decision on appropriate trading venues. Battalio et al. (2002) already outline the strategic importance of market selection, i.e. the appropriate routing of orders. In contrast to the US, where the routing decision has been analyzed by e.g. Bacidore et al. (1999) and Battalio et al. (2001), in Europe fragmentation of liquidity is rather new. This phenomenon has been induced by MiFID, which aimed at increasing competition among European financial markets. Before, most trading of European securities have been conducted at their home market. This finding is referred to as the home market principle (Schwartz and Francioni 2004). It has been reinforced in many EU member states by implementing rules obliging trades to take place at national exchanges only. Beyond suspending these concentration rules, MiFID provides an equal playing field by creating new trading platforms referred as multilateral trading facilities (MTFs) – the European counterpart to ECNs in the US. For the newly emerged trading venues such as Chi-X, BATS or Turquoise relevant market shares gains could be observed promptly (Fidessa 2012). In this regard, smart order routing technology might be one convenient mean to overcome the downside of new trading venues, i.e. increased fragmentation of liquidity. This innovation automates routing decisions and eases the implementation of self-directed order handling. Nevertheless, in case of European security markets, routing decisions have also to take adequate care of a fragmented post-trading infrastructure (Schaper 2008). **Paper 3** picks up this peculiarity and sheds light on the effect of fragmentation within post-trading on the potential of smart order routing technology. Therefore, **Paper 3** analyzes inefficiencies along the whole European securities trading value chain.

Nowadays electronic exchanges host automated traders, which operate at different magnitudes of responsiveness. At the same time, growing sophistication enables trading algorithms to handle not only larger but also more complex parts of the buy-side order flow. Accordingly, potential responsiveness improvements provided by low latency technology become increasingly important for the self-directed order handling of trading desks. One reason for this development is, that automated trading only has to obey physical principles such as the finite propagation speed of light within fiber optics[13]. Thus, latency, i.e. time required to propagate information, becomes a distinguishing factor. While in the past, latency was measured in dimensions of seconds, at the time of this research it was a matter of milliseconds (10^{-3}s) and nowadays even differences of microseconds (10^{-6}s) constitute a competitive advantage for traders (Martin 2007; Schweickert and Budimir 2009; CISCO 2006). Concerning this matter, Garvey and Wu (2010) analyze executions from traders located at different distances around New York between 1999 and 2003. They find lower transaction costs for traders domiciled geographically closer to the trading venue as well as those exhibiting lower latencies. Consequently, Martin (2007) reports that about 42,000$ per year are paid for low latency technologies such as co-locating[14] a single computer rack at NASDAQ. At the same time, he estimates that already an advantage of one millisecond can increase profits of a major brokerage company by 100m$ a year. These numbers refer to the new phenomenon of high-frequency trading. Contrary to algorithmic trading, which is one way to implement long term investment decisions, high-frequency trading is based on many, rather small profits gained by frequent trades. That way high-frequency trading exhibits short holding periods and aims at closing positions at the end of a trading day[15] (Aldridge 2010). While low latency technology is a natural necessity for high-frequency traders in order to stay competitive with their peers, the economic advantage of this technology with regards to the self-directed order handling of buy-side trading desks is hard to quantify. Even recent market microstructure research leaves this questions unanswered. Instead, it focuses on the effects of market-wide technology improvements to speed up information dissemination for all market participants (Hendershott and Moulton 2011; Riordan and Storkenmaier 2012; Easley et al. 2014) or the influence of high-frequency trading on traditional execution quality measures such as spreads, liquidity or volatility (Brogaard 2010; Cvitanic and Kirilenko 2010; Jovanovic and Menkveld 2011; Hasbrouck and Saar 2012). The only exception being Hasbrouck and Saar (2012), who vaguely notice that *"[i]t depends on both the risk borne over the delay duration and the effects*

[13]The propagation speed of light in vacuum is 299,792,458 $\frac{m}{s}$. In a conventional fiber optics light it is about 31% slower, due to the medium glass. But recently, researchers from the University of Southampton achieved a breakthrough, which allows the light to travel with 99.7% of its propagation speed in vacuum (Poletti et al. 2013). For that purpose, the fiber is made mostly of air. Nevertheless, one has still to cope with additional delays due to network infrastructure like switches, routers and amplifiers.

[14]By co-locating servers for trading algorithms near to an exchange's matching engine, latency caused by long distance signal propagation and delays due to network infrastructure is avoided. This kind of low latency technology is provided as co-location or proximity services.

[15]Further distinctions between algorithmic and high-frequency trading are provided by Gomber and Haferkorn (2013).

on participants' strategies" (p. 34). In an attempt to concretize their statement and to grasp the importance of low latency technology for the self-directed order handling of buy-side trading desks, **Paper 4** is devoted to analyze the general impact of latency on market participants.

While the transparency of e-CLOBs helps to increase market efficiency, it aggravates the order exposure problem (c.f. section 2.2) for institutional investors at the same time. Accordingly, in order to successfully handle block orders that exceed the capabilities of trading algorithms[16], buy-side institutions strive for alternative less transparent channels for their order handling. One such anonymous and entirely confidential alternative are dark pools, which represent an IT-based extensions of traditional upstairs markets (Gresse 2006). While dark pools are said to be suitable for buy-side traders with a desire of low information leakage (Harris 2003), their fill rates are rather low. Generally, they range below the 10% level (Næs and Ødegaard 2006). Further, achievable execution prices depend mostly on the market model a dark pool employs. For example, crossing networks import their price from a predefined reference market at randomized points in time (Conrad et al. 2003). For other dark pool types, such as negotiation dark pools, the actual execution prices are not clear beforehand. On this basis the information, whether and under which conditions negotiation dark pools lead to beneficial executions, is essential for their successful integration to a self-directed order handling. Therefore, **Paper 5** develops a benchmarking approach for the analysis of such opaque channels.

3 Research Methodology and Datasets

3.1 Literature Review

The first research question, on how to structure a systematic approach describing the usage of new channels, frames the topic of this thesis. For this purpose a literature reviews is chosen within **Paper 1** (Creswell 2003). This is motivated by the vital role this method plays for identification of knowledge gaps and its support for building on research already performed (Webster and Watson 2002). An important aspect of literature reviews is a description of their conceptualization. That way, their scope and intended limitations are illustrated and consequently its reusability is eased (Fettke 2006):

The review in **Paper 1** aims at an interdisciplinary research question. Accordingly, it covers not only IS research (vom Brocke et al. 2009), but also finance and computer science articles. Nevertheless, as the new IT-driven option for institutional investors to insource their trading begins in the late 1990s, the review is not intended to be time-wise complete (Fettke 2006). Instead, it focuses on literature on innovations along the securities trading value chain after 1990, by the time when completely

[16] Generally speaking, one might characterize the slicing of an order by trading algorithms as an aggregation of liquidity over time or alternatively as an adjustment of the order itself to fit into the trading venue's underling market mechanism in order to avoid market impact.

electronic exchanges evolved. Based on this setup a topic-centered literature review is performed. To grasp all relevant aspects and their impact on institutional equity trading, a second review is performed. Based on market microstructure literature, all steps required to facilitate the actual execution of a buy-side order are reconstructed. On this basis the employed search topics are chosen. The market microstructure related decision parameters and their impact on institutional equity trading include: trading styles, different market models, the selection of markets – e.g. the order routing decision – and the various aspects of execution quality.

To assure that all relevant entities, parameters, processes and involved interdependencies are considered, practitioner-oriented literature is considered as well. In this regard, an industry screening is used to outline the available innovations and their interplay. It is performed on different stages ranging from potential trading software, technical infrastructure and protocols such as FIX up to options how to connect to security markets. Eventually, different kinds of alternative trading venues are examined.

On this basis, the structured approach of an OCM framework is conceptualized. In a final step, the framework is discussed in expert interviews. That way, not only its suitability is backed, but also operational aspects are added, which are not common in academic literature.

3.2 Quantitative Survey

After identifying aspects relevant for the usage of new channels and defining the OCM framework, the second research question aims at factors which drive or inhibit process owners from setting up such a framework. In doing so, the focus is laid on the strength of the impact each factor has as well as generalizability. Thus, a quantitative approach is chosen in **Paper 2**. To analyze the interplay among different factors a causal model is developed (Rigdon 1998). As it incorporates latent constructs – variables not directly observable – such as process owners' perceptions concerning properties of new channels, the causal model is tested via a structured equation model (SEM). This permits latent constructs to be investigated via directly observable (manifest) indicators, collected in a quantitative survey.

Model Assumptions

The second research question relates to classical IT adoption research. As a theoretical basis for the verification of different drivers, two prominent models on IT utilization are selected: Firstly, TAM by Davis (1989) to grasp the process owner's believes and attitudes. Secondly, the theory of Task-Technology Fit (TTF) by Goodhue and Thompson (1995) to overcome TAM's potential weakness in accounting for the task characteristics. These two models are combined, based on the proposal made by Dishaw and Strong (1999), to take advantage of the two different perspectives.

The newly created model allows accounting for external factors. For that purpose its TAM core is further extended. In doing so, the model resorts to two TAM predecessors: the Theory of Reasoned Action (TRA) by Fishbein and Ajzen (1975) as well as its extension, the Theory of Planned Behavior (TPB) (Ajzen 1991). Based on TRA the subjective norm construct is reintroduced. It is labeled as competitive pressure and shall account for social pressure to use IT in an organizational adoption context (Taylor and Todd 1995). Due to the fact that some process owners might lack volitional control over their adoption (Schwartz and Steil 2002), the construct of perceived behavioral control is taken from TPB. It is used to measure the impact of contractual inhibitors. This might be soft commissions agreements or CSAs for the present case of securities trading (Schwartz and Francioni 2004).

The intention to introduce the TTF construct is twofold: On one hand, results by Lucas and Spitler (2000) indicate in case of brokers that job requirements are potentially an explanatory variable next to a standalone TAM. Additionally, TTF is said to exhibit high explanatory power for work-related tasks like trading (Dishaw and Strong 1999). On the other hand, it is intended to further verify the importance of order handling characteristics already elaborated in **Paper 1**. Basically, these are the three order dimensions *size*, *execution urgency* and *information leakage risk* (Ende et al. 2007). For that purpose, the TTF construct is introduced as a formative one.

Empirical Analysis

As new channels originate from the US and are still establishing themselves in Europe (EdHec 2005; Kentouris 2011), process owners from the 500 largest European institutional investors constitute the survey basis for evaluating the research model. To assure content validity, measures, based on a fully anchored 7-point Likert scale, are adapted from prior empirical studies whenever appropriate or developed during expert interviews. Afterwards, the questionnaire is pre-tested independently and negated control questions are implemented. Eventually, 48 out of 50 responses are used.

For the analysis the Partial Least Squares (PLS) method introduced by Chin (1998) is given precedence over covariance-based alternatives such as LISREL (Joreskog and van M. Thillo 1972). This decision is mainly based on the fact that the PLS approach allows incorporating both reflective and formative constructs within the analysis of one SEM model. Additionally, this method is said to be more suitable for explorative SEM models like the investigated one. Finally, PLS is free of distribution assumptions and even enables the analysis of smaller sample sizes (Chin 1998).

Bootstrapping with 500 samples is employed for the statistical model evaluation. Furthermore, for the reflective constructs, the analysis resorts to Chin (1998) and checks indicator reliability as well as convergent and discriminant validity. For the formative TTF construct, a five-step test procedure by Diamantopoulos and Winklhofer (2001) is used. This includes the review of content and indicator specification, indicator collinearity and reliability as well as external validity. In the end, the structural model is tested via the strength and significance of path coefficients as well as its explanatory power (R^2).

3.3 Simulation of Smart Order Router Technology

Paper 3 is based on a simulation. The unique feature of this approach is that it allows setting up controlled replications (Axelrod 2006), which enables a comprehensive market analysis on the potential of smart order routing technology. For that purpose outcomes of two different types of order specifications are required, while all other market parameters are kept constant: one employing smart order routing technology and the other one relying on common routing rules. Further, simulations support the analysis of how parameter changes effect results. In case of smart order routers, such parameter effects of interest are different transaction cost assumptions.

Bratley et al. (1987) define simulations as *"driving a model of a system with suitable inputs and observing the corresponding outputs"* (p. ix). For the current example, such inputs are actual order executions as well as order book situations at alternative execution venues and the model is the smart order router engine itself.

Model Assumptions

Similar to **Paper 2**, the example of an European institutional investor is assumed. In this case, potential adopters of smart order router technology are faced with prevailing fragmentation within the European post-trading infrastructure (Schaper 2008). To capture all effects of the routing decision on the trading as well as on the post-trading stages, the analysis takes a process-oriented perspective. Consequently, **Paper 3** enhances the general potential vs. realized value framework proposed by Chircu and Kauffman (2000) for the case of smart order routing technology. The simulation approach employed is based on Weyland and Engiles (2003), who highlight this method's suitability to support the optimization of business process outcomes.

The core extensions of the potential vs. realized value framework are formed by two newly developed artifacts: a dynamic smart order router engine and a static transaction cost modeler. To determine the potential business value (Davern and Kauffman 2000), the smart order router is designed to simulate an optimal technology solution. That way it compares all actual executions with historical prices and volumes available at other trading venues. Trades, for which better potential execution prices at other venues can be found, are labeled as trade-throughs[17]. Cases, where the full trade volume can be executed at that better price, are referred to as full trade-throughs, those that could not, as partial trade-throughs. This is required as the available order book data is limited to the top level quotes (level one data) only.

[17] A trade-through describes a sub-optimal transaction where better-priced orders are available at a market but are not included in the transaction, i.e. *"the better-priced orders are 'traded through'"* (Schwartz and Francioni 2004, p. 232).

The potential business value is defined as the price improvement between the actual observed execution price and the best price realizable at an alternative venue (gross savings).

The second step focuses on barriers determining the realizable benefits. For smart order technology these are additional explicit transaction costs, incurred for completion of a gross trade-through at an alternative market. The transaction cost modeler, developed for that purpose, accounts for variable costs only, including explicit trading fees, costs for post-trading and (potential) cross-border transfer (Oxera 2007). Further, switching costs refer to the difference between the costs for the observed sub-optimal trade and those for the execution at an alternative market. In order to establish a general analysis framework, the transaction cost modeler employs two cost scenarios based on investor size. The first one as a low-cost boundary, assuming direct access to the respective post-trading infrastructure, and the second one as a high cost boundary, depending on intermediaries.

Empirical Analysis

With the emergence of Chi-X Europe in 2007, benefits of smart order routers were expected to materialize most rapidly in actively traded stocks. As a consequence, the focus is laid on constituents from the Dow Jones EURO STOXX 50 index as of October 2007. The data itself covers four weeks, two in late 2007 and two in early 2008. For the analysis, only such European markets[18] are considered, which offer direct market access for a smart order router.

The basis for the analysis are order book market data provided by Thomson Reuters. These data consist of all updates of best bid- and ask-limits. They also contain trade prices with their respective volumes and time stamps with a time granularity of one second. Unfortunately, no indications of trade direction are incorporated. To overcome this, trade classification rules according to Lee and Ready (1991) are used. Trades, which cannot be classified unambiguously, are discarded. As the analysis is focused on continuous trading, data from call auctions as well as security buffers around these auctions are removed. This should safeguard results from being affected by switches between operating modes of a market. From a total of $9,163,780$ trades $1,152,875$ trades or 12.58% have been excluded.

To investigate the efficiency within the trading process, statistical tests are performed. They are based on the assumption of an efficient overall market (Schwartz and Francioni 2004), where trading costs consume gross savings. Accordingly, after switching costs sub-optimal order executions should not reach a significant level. To verify this, for each cost scenario mean values of gross savings are compared to those of switching costs. That way, three cases can be distinguished: (1) optimally

[18] The ten markets chosen are: Bolsa de Madrid, Borsa Italiana Milan, Chi-X Europe, the four Euronext (EN) markets (Amsterdam, Brussels, Paris, and Lisbon), NASDAQ OMX Helsinki, SWX Europe and Deutsche Börse XETRA.

executed orders, (2) trade-throughs with positive net savings and (3) trade-throughs where switching costs offset gross savings.

To test the overall level of net trade-troughs the null hypothesis (H_0) below is tested, under the assuption that the test statistics exhibits a Student's t-distribution. In order to back the results due to varying observation numbers, a second non-parametric test is performed, too.

$$\mathbf{H_0:} \text{mean(gross savings)} \leq \text{mean(switching costs)}$$

3.4 Simulation of Low Latency Technology

The requirements for measuring the potential of low latency technology are like those of analyzing smart order routing technology (cf. 3.3). However, the investigation has not only to take into consideration effects of latency on actual trade outcomes but also on orders, which cannot turn into trades due to latency. Unfortunately, the exact measurement of the latter effect depends on individual strategies employed. Following Axelrod (2006), simulation can alleviate this issue by a *"simple model that provides an important insight into a general process"* (p. 93). For latency effects such a simple model might be represented by basic strategies, to which real investment strategies can be decomposed without losing generality. In that regard, suitable inputs (Bratley et al. 1987) would be two kinds of order book situations: one from which the order submission is derived from and the other one encountered when the order actually hit the order book, i.e. after a predefined latency. Based on the general traits of the latency effects deduced from such a simulation, conclusions on actual investment strategies can be drawn. That way the simulation method chosen for **Paper 4** can be perceived as a third approach besides deduction and induction, which *"generates data that can be analyzed inductively"* (Axelrod 2006, p. 94). In **Paper 4**, the focus of this data generation is laid on the identification of statistical properties and patterns, which the impact of latency exhibits.

Model Assumptions

As first step, basic dimensions of orders such as execution urgency – either active (immediate execution via market orders) or passive (via non-executable limit orders) – and initiator side, i.e. buyer- or seller-initiated, are looked at (Harris 2003). On that basis, four elementary trading strategies, representative for typical trading strategies, are introduced. Before models of these strategies are designed for the simulation the relevant order book parts are selected. As speed advantages of low latency technology exceed the limits of human reactions, the approach taken resorts back to results on algorithmic trade patterns by Gsell and Gomber (2009). They show that trading algorithms typically target merely the top of the book.

The simulation models take the perspective of Clemons (1991) and aim at deriving the business value of low latency technology by assessing its impact on traders who do not have access to it, i.e. due to the unreliability of the observed market situations caused by latency. For that purpose the quantitative performance metric $p_{fluc}(x)$ is defined *"as the probability of a change in either the best ask or bid limit or the corresponding volumes at the top of the order book"* (Ende et al. 2011, p. 4) within x milliseconds.

This definition of $p_{fluc}(x)$ is based on the concept of *order book fluctuation*. It does not only concentrate on price changes like standard measures such as volatility, bid-ask spreads or the midpoint do, but also considers volume changes within the book. To avoid overestimations of the derived probabilities, the metric only counts such volume alterations where the limit price remains stable. This is due to the fact that each limit price change also typically includes a volume change.

Altogether, $p_{fluc}(x)$ is analyzed for five cases: one accounting for all kinds of changes and one for each of the four elementary strategies, which pays attention only to unfavorable changes for that single strategy in question.

Empirical Analysis

For the evaluation of the metric $p_{fluc}(x)$, the focus is laid on instruments which exhibit high algorithmic trading activity. For the analyzed XETRA system, this is the case for index members of the DAX 30 (Schweickert and Budimir 2009). To grasp a cross-sectional overview, three pairs of different free-float capitalization are investigated. To assure that no extreme market activities or unusual overall market volatility bias the analysis of the new metric, the sample period includes normal trading activity of two weeks starting on August 31st, 2009. The data basis and safeguards employed are similar to those of section 3.3. The only exception being available time granularity, which is one millisecond for the current case.

The empirical analysis of $p_{fluc}(x)$ includes typical latencies (Schweickert and Budimir 2009) from 5 to 100ms with a granularity of 5ms steps. Further, latencies of 1 and 2ms are included as lower boundaries. For these latencies also average limit and volume changes are investigated, to grasp the actual latency impact, conditional on the fact of being affected by an unfavorable order book change.

The simulation results of $p_{fluc}(x)$ are analyzed for day patterns. For this purpose, different interval lengths are checked. Within each interval, a sliding window is used to derive the observable number of relevant order book changes. Then, the number of observed changes is divided by the whole number of milliseconds within the interval. The final estimator for $p_{fluc}(x)$ is derived from the average of these ratios for the ten trading days for each interval. For the calculated $p_{fluc}(x)$ measure descriptive statistics are provided. They range from graphical presentations of the influence of market capitalizations to a derivation of the functional impact of latency on $p_{fluc}(x)$ via a log-linear regression. Finally, to evaluate the impact of being hit by an order book change, average volume and price changes are investigated via regressions for patterns during the trading day.

3.5 Empirical Analysis of Negotiation Dark Pools

The typical approach to avoid market impact is a crossing network, a special case of dark pools (Schwartz and Francioni 2004). While for these alternative trading venues the derivation rules for the execution prices are clear beforehand, for negotiation dark pools this is not the case. Accordingly, the question arises how their negotiation mechanism affects potential market impact and execution prices. For the investigation conducted in **Paper 5** an empirical analysis approach is chosen.

Model Assumptions

The proposed metric is based on the concept of *price improvements (PI)* in comparison to quoted prices at a reference market (benchmark). Therefore, *PIs* are defined as the difference of the half spread of the reference market and the absolute price difference of the trade price ($P_{Venue,i}$) and the reference market's midpoint ($P_{RMMP,i}$), where i distinguishes the trades observed:

$$PI_i = halfspread_i - \left|P_{Venue,i} - P_{RMMP,i}\right|$$

If the execution price is within the bid/ask spread of the reference market, *PIs* are positive. Otherwise they are negative, as they would have created market impact, if they would have been traded at the reference market. In order to account for different quotations the analysis is performed relative to the midpoint.

The above definition of *PIs* for negotiation dark pools implicitly makes assumptions on the price of the reference market and the initiator side of the trade:

Like crossing networks, the price at a reference market serves as a surrogate for the fair equilibrium value of an instrument (Hendershott and Mendelson 2000). Accordingly, the selected reference market should exhibit the best possible price discovery. Typically, the quality of execution prices is positively correlated to the trading volume of a market. This is established by high volumes being perceived as a tool for the incorporation of as much information as possible (Schwartz and Francioni 2004). As in Europe trading of a security is principally concentrated at its home market, this market would be a natural choice.

The twofold assumptions concerning the initiator side of the considered negotiation dark pool trade are: Firstly, the initiator is expected to provide price concessions in order to attract a counter party (Harris 2003). Secondly, the benchmark metric is designed to be a conservative one. According to the zero-sum nature of trading, either both sides of a trade are equally attractive (trade at the fair equilibrium price, i.e. the midpoint of the reference market) or one is perceived as being more favorable than the other (Sarkar and Schwartz 2009). On this basis, the metric is designed to concentrate on the less attractive side of the trade by assuming an observed price below (above) the midpoint of the home market to be sell-initiated (buy-initiated).

Empirical Analysis

Due to its unique market model and high trading volumes (Thomson Reuters 2012), the negotiation dark pool Liquidnet Europe is chosen. For the analysis, two data types are used: At first, execution reports from Markit BOAT[19], which include negotiated trade prices, volumes as well as actual time stamps of Liquidnet Europe trades. The second type comprises corresponding order book snapshots for the home markets. As dark pool executions are seldom expected to take place (Harris 2003), a broad set of assets from the DOW JONES EURO STOXX is selected. It includes three subsamples of 64 instruments, based on free float capitalization. The analysis period starts on June 6^{th}, 2008 and covers 15 months. It includes $3,576$ trades with an overall volume above 8.8bn€. To avoid adverse effects due to strong price changes, only continuous trading is kept for the covered home markets and a security buffer of two minutes is included. The final analysis covers 97.5% of the trade value of the initial sample.

Based on the above data, statistical tests are performed to evaluate (1) the advantage of trades at negotiation dark pools such as Liquidnet Europe as well as (2) the determinants of the observed *PIs*. Similar to section 3.3 t-tests are employed.

To test whether significant *PIs* exist for negotiation dark pools, the null hypothesis $H1_0$ is evaluated.

$$\mathbf{H1_0:} \text{mean}(relativePI) \leq 0$$

Three additional hypotheses are formulated to analyze the determinants of *PIs*. The first question of interest is whether observed *PIs* are related to trade sizes. At traditional exchanges one can observe that the larger an order becomes the higher its market impact is. This yields to the assumption that block trades are being executed at inferior prices (O'Hara 1995). To test whether negotiation dark pools can avoid market impact cost, the null hypothesis $H2_{a0}$ is tested. Here, trades are classified as block trades which exceed 15% of the respective average daily security trading volume of the last 30 trading days before the trade (Kissell et al. 2003).

$$\mathbf{H2_{a0}:} \text{mean}(relativePI_{block}) = \text{mean}(relativePI_{non-block})$$

The second null hypothesis $H2_{b0}$ is formulated to investigate whether the realized *PIs* are distributed asymmetrically as market microstructure theory suggests for traditional exchanges (Keim and Madhavan 1997; Bikker et al. 2007).

$$\mathbf{H2_{b0}:} \text{mean}(relativePI_{buy}) = \text{mean}(relativePI_{sell})$$

With the final null hypothesis H2c0 the relation between *PIs* and market capitalization is targeted. In this regard, the question is whether lower market capitalizations and hence lower liquidities typically imply higher market impact costs (Stoll 2001).

[19]Markit BOAT is a trade reporting service allowing Liquidnet Europe, which operates as MTF, to fulfill its MiFID post-trading transparency requirements.

To test this typical observation for traditional exchanges, the medians of the three free float capitalization-based samples employed for this research are compared.

$$\mathbf{H2_{c0}}\text{: median}(relPI_{large-cap}) = \text{median}(relPI_{mid-cap}) = \text{median}(relPI_{small-cap})$$

For the last null hypothesis $H2_{c0}$, unequal variances are identified by a corresponding Bartlett-Test. Thus, an independent sample Kruskal-Wallis Test (H-test) is employed.

4 Main Results

The following subsections briefly summarize the results obtained within the papers of this cumulative thesis.

4.1 Paper 1[20]: Definition of an OCM Framework

In **Paper 1** existing literature on institutional equity trading is extended by a framework for setting up self-directed order handling. The purpose of the framework is to delineate how institutional investors can gain control by becoming less dependent on their brokers. In summary, this should increase efficiency of their OCM. Concerning that, new channels are central.

As first step, OCM[21] is defined as *"...the process of information gathering, evaluation, decision and control regarding the setup of the overall trading infrastructure (strategic OCM) and the actual order routing implementation (operational OCM)"* (Ende et al. 2007, p. 708).

To further detail the framework, involved key entities, parameters, processes and their interdependencies are outlined. When compared to the traditional process of delegating orders to brokers, self-directed order handling increases process complexity at a trading desk (Hurewitz 2012). Apart from a higher demand on technological sophistication of institutional investors, infrastructure extensions are required and upcoming execution venues have to be handled. The same holds true for upcoming technology developments as well as new trading strategies. Therefore, the OCM framework consists of a structured approach, which breaks down OCM into a strategic and an operational part:

Strategic OCM[22] involves management decisions concerning the targeted trading setup. Therefore, it involves the gathering of information for a sophisticated selection of trading venues. The actual choice is based on a matching of characteristics of the order flow and the trading venues' capabilities concerning information leakage risk, transaction costs, fill rates as well as likelihood and immediacy of execution. Further,

[20] B. Ende, P. Gomber and A. Wranik. An Order-Channel Management Framework for Institutional Investors. In: *International Conference on Wirtschaftsinformatik Proceedings (WI2007)*, volume 2, pages 705–722, 2007.

[21] Figure 5 on page 26 provides a decomposition of OCM responsibilities.

[22] An overview of the decision parameters for strategic OCM is provided in figure 7 on page 66.

for the final pool of trading venues strategic OCM has to establish the following aspects: connectivity, trading software, traders and technical infrastructure. Overall, this provides the framework for operational OCM on an order-by-order basis in daily operations.

The cornerstone of operational OCM is to match characteristics of orders to those of venues. For this purpose, a classification scheme[23] of five order types is proposed. The scheme is based on a distinction of orders along the three dimensions size, information leakage risk and level of execution urgency. Furthermore, the realization of operational OCM has to cope with order constraints. How this can be achieved, is shown by introducing a three-step approach consisting of order classification, actual order-channeling and the reaction to order-channeling outcomes.

4.2 Paper 2[24]: Adoption Decision for an OCM Framework

The analysis of a buy-side survey conducted among process owners at the largest European institutional investors reveals the following three main findings:

1. The decision to adopt an OCM framework is driven rather by internal than external factors. For the two analyzed external factors competitive pressure and contractual inhibitors, the expected effects on the intention to adopt can be observed, although their influence turns out to be weak. However, performance expectations are the strongest predictor for intention to use. While this observation is in accordance to TAM literature (Venkatesh et al. 2003), in case of effort expectations merely a rather weak effect on performance expectations can be shown.

2. The perceived fit between the characteristics of the order flow and the technologies' capabilities plays a central role. TAM for example does not fully mediate the effect of TTF despite TTF being the strongest predictor for performance expectations and usage. However, the explanatory power of TTF regarding effort expectations is rather weak. This means that the perceived fit of a technology is the major direct and indirect determining factor of usage. Hence, TTF represents the starting point of a strongly significant chain of causations for the mode of action among internal factors.

3. The relevance of the order classification scheme presented in **Paper 1** is highlighted. This is attained by confirming the validity of the three order-difficulty determinats it is based on: For execution urgency and information leakage risk significance is proven within the analysis of the formative TTF construct, while the relevance of the third determinant of order size is obvious. Besides, to better understand the perceived fit, process owners shall focus on whether trading

[23] Table 3 on page 73 depicts the order classification scheme.

[24] B. Ende. IT-Driven Execution Opportunities in Securities Trading: Insights into the Innovation Adoption of Institutional Investors. In *European Conference on Information System Proceedings (ECIS 2010)*, Pretoria, South Africa, 2010.

innovations are capable to satisfy their requirements for more trading control, high anonymity and varying urgency demands.

4.3 Paper 3[25]: Business Value of Smart Order Router Technology

Against the background of new trading venues such as Chi-X and a more fragmented trading landscape due to MiFID, **Paper 3** analyzes the efficiency of the European trading process. For that purpose, a potential vs. realized value simulation framework (Chircu and Kauffman 2000) for the case of smart order routers is proposed. Within this framework, the potential of this technology to improve the overall trading outcome is shown. Therefore, three cost scenarios are employed: no costs, direct access (low costs) and intermediated access (high costs). Results from the intermediated (high costs) scenario reveal that only large investors with direct non-intermediated access have the ability of leveraging this potential.

Moreover, results highlight that the extent of prevailing sub-optimal executions is economically relevant and statistically significant. For these executions better prices are available at another market even for the cost scenarios. In the first instance, based on a total of 8,010,905 trades[26], an assumed no cost scenario leads to 6.71%, (absolute: 537,764) which can be executed better with their full volume (full trade-throughs) and 6.45% (absolute: 516,797) at least with a part of their volume (partial trade-throughs). This constitutes a potential for savings of 9.50m€ within the sample period. In relative terms, these are 7.54bps compared to the total trade-through value and 0.36bps of the total traded value. Most of this potential prevails even for the intermediated access (high costs) scenario, where savings amount to 5.9m€. On average, this allows for savings of 26.83€ per trade-through, which corresponds to 10.17bps relative to total trade-through value of the intermediated cost scenario and 0.23bps relative to total traded value. However, only 1.41% of the trades can be identified as full trade-throughs and 1.34% as partial ones.

From an overall market perspective, this high cost scenario shows that for smaller investors the potential of smart router technology is overcompensated by explicit costs. However, when analyzing individual securities, this is only partly the case. Thus, trade-throughs in Europe cannot be explained by transaction costs alone. One potential explanation might be that a certain number of investment firms still resort to the home market principle (Schwartz and Francioni 2004) and apply static routing to one pre-defined market per security only. As for Germany, Gomber et al. (2012) have already shown that investment firms prefer exactly this minimal static routing implementation to fulfill their best execution obligations. This also matches with the argumentation by Foucault and Menkveld (2008), who state sub-optimal trade executions on Dutch markets to be caused by a lack of automated routing decisions.

[25] B. Ende, P. Gomber, M. Lutat and M. C. Weber. A Methodology to Assess the Benefits of Smart Order Routing. In *Software Services for e-World, IEEE (IFIP) Advances in Information and Communication Technology*, 341(1), pp. 81–92, Springer, Boston, USA, 2010.

[26] These trades result from four weeks of trading data in late 2007 and early 2008 of Dow Jones EURO STOXX 50 constituents.

4.4 Paper 4[27]: Business Value of Low Latency Technology

The business value of low latency technology is tightly related to the strategy of an investor. Since tools, employed by expected profiteers such as high-frequency trading algorithms, are proprietary (Gomber and Haferkorn 2013), an implicit approach is derived in **Paper 4**. It resorts to the concept of order book fluctuations to measure the impact of latency on customers of an exchange. In general, results highlight that the business value of low latency technology is mainly driven by the employed investment strategy of the investor: While for retail investors price as well as volume effects are negligible; institutional investors have to take care of the profits associated with their trades. The lower these profits are on average per trade, the more valuable low latency technology becomes for them. Also this impact is increasing nonlinearly with latency.

On top of these overall results, the following five insights on the impact of latency are derived:

1. Among the observed changes within order books, pure changes for volumes occur twice as often as limit alterations. This indicates that standard measures such as volatility cannot fully capture the impact of latency. As a consequence of frequent volume changes, passive strategies based on non-marketable limit orders such as market-making are particularly exposed to the impact of latency.

2. The probability $p_{fluc}(x)$ of being affected by an order book fluctuation with a latency of x milliseconds exhibits a significant day pattern, which can be sketched as a modified U-shape. This is comparable to patterns observed for trading volumes (Stephan and Whaley 1990; Abhyankar et al. 1997). In contrast to those, an additional sharp decrease can be seen daily at about 14:30. The shape of the pattern is independent from the employed basic strategy. Concerning the magnitude of $p_{fluc}(x)$ passive strategies are facing higher probabilities than active ones, while no significant differences can be observed among buy and sell strategies.

3. The observed day pattern remains stable even for higher latencies, which only amplify its magnitude. In doing so, the amplification effect exhibits a slight concave shape. Via a log-linear regression, an increase of 1% in latency can be shown to raise the probability of being hit by an unfavorable order book change by 0.9%. This implies that the impact of latency increases, when overall latencies decline.

4. Instruments with higher market capitalizations exhibit a higher latency impact than low capitalized ones.

[27] B. Ende, M. C.Weber, and T. Uhle. The Impact of a Millisecond: Measuring Latency Effects in Securities Trading. In *International Conference on Wirtschaftsinformatik Proceedings (WI2011)*, Paper 116, Zurich, Switzerland, 2011.

5. Concerning changes of limit and volumes, which are faced due to latency, limit changes tend to decrease over the trading day, while no stable patterns for volume changes can be detected. Overall results show that for an exemplary active high-frequency strategy (Narang 2010), reported by the US high-frequency trader Tradeworks, solely due to the limit change costs of an assumed latency of 50ms, profits might diminish by 26%.

4.5 Paper 5[28]: Business Value of Negotiation Dark Pools

To make new trading venues accessible significant IT investments are required. To support the decision-making of institutional investors, **Paper 5** develops a post-implementation IT benchmarking approach (Doll et al. 2003). The introduced benchmark compares negotiation dark pool executions with prices available at traditional stock exchanges. It infers a positive price improvement when the negotiation dark pool execution is within the spread of the reference market.

As a first step, a descriptive analysis of trading data confirms academic literature in two ways. On one hand, execution sizes of negotiation dark pools such as Liquidnet Europe are significantly larger than what is defined as large-in-scale and corresponds to 500,000€ for highly liquid stocks (CESR 2008). Compared to trades at a traditional exchange such as XETRA, observed executions are even 475 times larger. On the other hand, it is difficult to find counterparties (Harris 2003; Næs and Ødegaard 2006), as the trade frequency is rather low. Within the analyzed 15 months period between June 6th, 2008 and September 14th, 2009 only 18 trades can be observed for an average DOW JONES EURO STOXX constituent. Basically, higher market capitalization leads to higher trade frequencies at the investigated negotiation dark pool.

By means of statistical analysis, the following two insights are gained:

1. The advantage of trading at negotiation dark pools such as Liquidnet Europe is shown. While average market impact costs are said to be 20bps for buy and even 30bps for sell orders (Bikker et al. 2007), executions at the exemplary negotiation dark pool exhibit even positive price improvements compared to available market prices with a median of 3.41bps.

2. The investigation of trade characteristics, which lead to such price improvements, proves larger executions (block trades) to lead to significantly higher price improvements. Furthermore, significantly different levels of price improvements are observable among different levels of market capitalizations. Hence, trades of small- and mid-cap instruments appear to be most beneficial at negotiation dark pools, as they come along with the highest price improvements. This observation differs with experience of traders at traditional exchanges,

[28] B. Ende and J. Muntermann. Assessing IT-Supported Securities Trading: A Benchmarking Model and Empirical Analysis. In *Americas Conference on Information Systems Proceedings (AMCIS 2010)*, Paper 476, BEST PAPER AWARD NOMINEE, Lima, Peru, 2010.

where lower market capitalizations and hence lower liquidity typically imply higher market impact costs (Stoll 2001). Finally, the side of a trade is analyzed (i.e. buy- or sell-initiated). While traditional exchanges exhibit asymmetric negative price movements (Keim and Madhavan 1997; Bikker et al. 2007), no significant differences among price improvements of buy- and sell-initiated trades can be proven for the analyzed negotiation dark pool trades. This might be due to more patient traders at negotiation dark pools, while at traditional exchanges *"[b]locks are sold, not bought"* (Kraus and Stoll 1972, p. 573), which leads to higher price concession for the selling side.

5 Contributions to Literature and Practice

While proposing a framework on how-to-make-use of new trading technologies, this thesis has multiple target groups: To academia it contributes by introducing new methods of analyzing upcoming trading technologies and assessing their impact on the securities trading value chain. For practitioners such as institutional investors or regulators valuable insights are provided concerning relevant factors for their decision-making. The lessons learned regarding literature and practice are outlined in the next two subsections.

5.1 Contributions to Literature

This thesis refers to theories of technology adoption and business value of IT research. Consequently, for the domains of these theories new methods for analyzing innovations are introduced. In doing so, new insights into market microstructure theory are provided. The individual contributions to each of these theories are as follows:

Technology Adoption

The adoption decision concerning a bundle of new channels in securities trading is analyzed in **Paper 2**. It therefore extends the scarce literature on adoption research in this domain (Lucas and Spitler 2000; Lai and Li 2005; Khalifa and Davison 2006). Additionally, it breaks the limitation of previous literature in analyzing the adoption of only one singular technology at once. Furthermore, TAM is successfully extended in two aspects: On the one hand, by rejoining it with its predecessors to grasp external factors such as competitive pressure and contractual inhibitors. On the other hand, strong support is provided for the proposal by Dishaw and Strong (1999) to integrate TAM with the TTF. In this regard, **Paper 1** and **2** introduce and successfully test a formative formulation of TTF for the domain of security trading. Moreover, perceived fit of a technology is proven to be the major direct and indirect determining factor of usage in the chosen research context of a work-related task. Thus, TTF represents the starting point of a strongly significant chain of causations within internal adoption factors. Testing this observation on a generalized basis might be a promising starting point for further research.

Business Value of IT

Paper 3, 4 and 5 are devoted to analyze the business value of innovations. In this regard, literature on performance metrics (Hitt and Brynjolfsson 1996) is enriched for innovations such as smart order routing (**Paper 3**), low latency technology (**Paper 4**) and negotiation dark pools (**Paper 5**). In **Paper 3** a simulation framework is introduced, which allows tracking optimizations of business process outcomes (Weyland and Engiles 2003) along the whole securities trading value chain. This is done against the background of increasing European market fragmentation. Moreover, the presented methodology extends the approach of a potential vs. realized value framework by (Chircu and Kauffman 2000) for the domain of securities trading. **Paper 4** depicts how the impact of latency on actual investment strategies can be simulated (Axelrod 2006). Therefore, the perspective of investors is taken, who do not have access to an innovation (Clemons 1991) – low latency technology for the present case. Further, a model of four basic trading strategies is introduced to simulate the impact of latency on their actual investment strategies. In the end, **Paper 5** develops a post-implementation IT benchmarking approach (Doll et al. 2003) for negotiation dark pools, which leave execution prices unclear beforehand. Therefore, market prices of traditional exchanges are employed to derive a reference for such alternative trading venues.

Beside these methodological extensions, results highlight that all three investigated innovations provide additional business value. But they simultaneously exhibit entry barriers tightly related to investor size. Based on the theory of competitive strategy (Porter 1980) such barriers allow profitability increases to remain sustainable (Philip et al. 1995).

Market Microstructure

Although taking a business value of IT perspective the analyses outlined within the **Papers 3, 4 and 5** also contribute to market microstructure theory:

In **Paper 3** research on execution quality and cross-market trading, which is mostly US centered, is extended. There, in contrast to Europe, post-trading infrastructure is centralized. Accordingly, research such as Bacidore et al. (1999) or Battalio et al. (2001) is merely able to cover the described no-cost scenario as it compares trade prices with quotes from competing markets. The European post-trading landscape, however, is fragmented. This results in significant transaction cost differences when switching from one market to another. Since in case of the US explicit transaction costs are not needed and thus ignored, a direct comparison with the European setup is not possible. The novation within the simulation approach, however, incorporates a transaction cost modeler: Inefficiencies caused by the fragmentation of the European post-trading landscape as indicated in Giovannini Group (2001, 2003) are taken into account and are quantified for the first time. Beyond that, comparing results from the no-cost and cost scenarios allows to measure the impact of those inefficiencies within the order routing decisions. Therefore, the significance of investor size can be proven in regard to the ability of leveraging the potential of smart order routing technology. In addition gross trade-throughs can be clearly highlighted as not being explainable by transaction costs alone.

Paper 4 shows that standard measures for market quality such as volatility are no appropriate means to evaluate the impact of latency. The reason behind is that they omit changes in volumes, which occur twice as often as those in limits do. Consequently, they do not account for an important aspect, especially for passive traders. Therefore, the new concept of order book fluctuations is introduced, which is based on the unreliability of the observed market situations. To quantify this effect of latency a quantitative performance metric is derived, which captures the probability of being hit by an unfavorable change in the order book. Empirical analysis shows that this probability has a concave functional relationship to latency. Further, the impact of latency depends on the strategy employed as well as on the time of the day.

Paper 5 provides important empirical insights into the literature of dark pools such as the works of Hendershott and Mendelson (2000), Næs and Ødegaard (2006) or Gresse (2006) as it is the first, which investigates innovative dark pool negotiation mechanisms: Market microstructure theory can be confirmed in so far as negotiation dark pools exhibit extraordinary large execution sizes. However, differences compared to trading outcomes at traditional exchanges are identified, too. Neither significant price concessions for trades in lower capitalized instruments (Stoll 2001) nor differences between the market impacts of buy- and sell-initiated block-trades (Keim and Madhavan 1997; Bikker et al. 2007) can be observed. Overall, results highlight that despite mechanisms to negotiate individual execution prices for each trade, the majority of executions take place at the midpoint. In this respect, the usage of the exemplary negotiation dark pool mechanism is mostly comparable to traditional crossing networks.

Lastly, within **Paper 1** and **2** a figurative contribution to market microstructure theory is made by highlighting that potential users of innovations strive for more trading control, high anonymity and solutions, which satisfy their varying urgency demands.

5.2 Contributions to Practice

The thesis at hand primarily addresses decision-makers at institutional investors responsible for the trading process and market regulators to a certain extent:

At first it is outlined how new channels can enable institutional investors to insource their order handling instead of delegating it to brokers. In this regard, the OCM framework defined in **Paper 1** aims at increasing trading control by a self-directed management of order handling. Hereto, it identifies aspects relevant for the design and implementation of an in-house trading process. While **Paper 1** outlines the general framework, **Paper 2** deepens the strategic adoption decision. To this end, general advice is provided concerning factors relevant for the configuration of an in-house order handling. Basically, potential adopters shall mainly focus on the fit between capabilities of relevant innovations and requirements of their order flow. In this regard, relevant dimensions are need for more trading control, anonymity and varying urgency demands. On the other hand, those investors who have already established their OCM can compare their decision-making with their peer group's perceptions. In **Papers 3 to 5** insights from a more operational perspective are shown. Within not only means to evaluate innovations are introduced but the papers also provide an in-depth discussion of exemplary technologies to which they are applied. That way, the simulation approach developed in **Paper 3** enables investors to assess the benefits of smart order routing technology. Decision-makers can constantly track the suitability of this innovation for their trading and their actual access setup. Therefore, they might adopt the proposed simulation approach for their historical order flow and recalculate the more applicable cost scenario – either intermediated high-cost access or non-intermediated low-cost access – with their own proprietary cost figures. The measurement methods introduced in **Paper 4 and 5** support the evaluation of decision makers (so does **Paper 3**) while setting the focus on low latency technology and alternative trading venues. In doing so, **Paper 4** concentrates on general features of trading strategies, which let low latency technology become essential. At first these technologies exhibit a higher relevance for passive strategies such as market-making. The lower the profits associated to each trade of a certain strategy become, the more they depend on low latency technology. However, for strategies, which follow long-term profits, the benefits of such technologies seem to be rather negligible. On the other hand, in case of negotiation dark pools, **Paper 5** highlights particularly advantageous trade characteristics such as lower instrument capitalizations and the absence of higher price concessions for sell-initiated block-trades.

While all three investigated innovations provide additional business value, institutional investors should bear in mind size-related preconditions, which are required to benefit from these innovations: **Paper 3** highlights that due to the fragmented post-trading infrastructure in Europe the benefits of smart routing technology is mostly limited to large investors, who have direct non-intermediated access to the post-trading facilities of foreign markets. **Paper 4** proves low latency technology to provide value only for market participants issuing a sufficiently high number of trades, whereby each one provides only a relatively small, short-lived gain. Finally, when considering negotiation dark pools (**Paper 5**), the requirement for suitable orders is outlined as to be large and not urgent, as it is hard to find suitable counterparties. On top, investors also have to exceed a size threshold of 500m$ AuM, as they would otherwise not be able to access this liquidity pool.

Paper 3 provides valuable input for market regulators who are consistently reviewing and reworking MiFID, which leads to the recent MiFID II sign off. For this target group, a method to monitor the efficiency of order executions at European financial markets is provided. As fostering competition among European markets has been one major goal of MiFID, regulators can rerun the different cost scenarios to deduce not only whether inefficiencies prevail, but also to track down whether these stem from the trading or post-trading stage. Accordingly, they can concentrate their efforts on refining MiFID for the former case and the Code of Conduct for the latter one.

6 Limitations and Research Outlook

6.1 Limitations

Generally speaking, limitations within the presented research originate either from methodological decisions taken or data availability:

Methodological issues include the limited testability of the OCM framework introduced in **Paper 1**. To overcome this, expert interviews are employed to verify its plausibility. The parameters proposed for the order classification scheme undergo statistical tests within the quantitative survey of **Paper 2**. Nevertheless, as the framework is based on literature reviews and an industry screening in mid-2006, it can only grasp innovations available at that time. One example of a subsequent concretization is the analysis of low latency technology performed in **Paper 4**. It shall adequately account for the more recent phenomenon of high-frequency trading.

Concerning data availability, institutional investors are anxious not to reveal any information, which would allow reverse engineering of their investment strategies. This in turn, would enable others to take advantage from their trade interests (Harris 2003). In tangible terms **Paper 2** has to cope with a respond rate of 10% (50 out of 500) as many process owners refer to their employer's policy not to participate in any survey. However, with a coverage of 33% of the sample's total AuM, these respondents represent the targeted larger institutional investors. As the fraction of process owners employing new channels also corresponds to previous descriptive studies such as EdHec (2005) and Financial Insights (2005, 2006), no systematic bias is expected. Nevertheless, in line with Goodhue et al. (2006) the data sample size of **Paper 2** restricts conclusions on significant paths only. While this should suffice to back the conceptual order classification scheme from **Paper 1**, no final conclusion on the effect of effort expectancy on intentions can be made. In this cases the power of the test might have been too low.

The **Papers 3 to 5** intend to develop metrics for evaluating the business value of selected innovations. In this regard, the data snapshots chosen aim at exploring the general traits of these metrics. Thus, while well-considered only limited instrument scopes and time windows are covered. Bearing in mind the increased fragmentation at European securities markets, the generalizability of figures from **Paper 3** is limited. This is due to the fact that the analysis within **Paper 3** is supposed to investigate the potential of smart order routing technology directly after MiFID coming into effect during a time where market fragmentation was rather limited. Further, the available dataset for **Paper 3** has only limited precision. Firstly, because its time granularity is one second, secondly it only contains level one data, i.e. limits and volumes from the top level of the order book. As typical market data also lacks trader identities, different assumptions and estimations are required to facilitate considerations of transaction costs. As these always come along with some kind of subjectivity, the final approach tries to track overall saving potential for smart order routing technology from a low and a high cost perspective (c.f. 3.3). These perspectives are gross of the one-off installation costs a smart order router bears, as such costs are not publicly disclosed. Nevertheless, by replicating the presented simulation approach potential adopters might judge the potential of smart order routing technology for their trading characteristics and against their variable and procurement costs.

Similar to **Paper 3**, the investigation of low latency technlogy in **Paper 4** is based on order book snapshots. It therefore lacks trader identities, which are necessary to link individual transactions to an individual strategy. As the impact of latency depends on such strategies, a simple simulation model based on four basic strategies (c.f. 3.4) is introduced. While this approach allows to draw general conclusions on the impact of latency, a monetary quantification still requires precise knowledge of the actual strategy.

A final limitation of the results of **Paper 5** is their dependence on two main assumptions (c.f. 3.5), which might bias implications. To secure their validity, they are backed by market microstructure theory. That way, the derivation of the benchmark prices resorts to the home market principle. Further, the determination of the initiator side is based on the rational from traditional exchanges that trade initiators are willing to pay price concessions.

6.2 Research Outlook

By formulating the OCM framework the thesis at hand introduces a new research aspect. While innovations are continuously evolving, the changes within the intermediation relationship between the buy-side and sell-side induced by technology adoption are still in progress. Bearing that in mind, future research can either continue the work started by the research papers presented in this thesis or extend them by breaking new ground in the context of OCM:

Future research might enrich the factors used within the analysis of the adoption decision concerning new channels (**Paper 2**) to further illuminate effort expectancies. Regarding this factor, the employed model exhibits only a rather weak explanatory power. Bearing in mind the profound interventions in the implementation of an institutional investor's core investment process, when setting up a self-directed order handling, it might be worth to investigate different risk aspects. Especially recent incidents are related to automation along the whole securities trading value chain like: AXA Rosenberg's failure to identify, correct and properly communicate an erroneous risk factor coding (SEC 2011), the automated trading glitch by Knight Capital after a software update (Strasburg and Bunge 2012) or the recent outages of NASDAQ (Kiernan 2013). All such incidents have either severe financial or at least reputational consequences. In line with previous research such as Featherman and Pavlou (2003) and Gewald et al. (2006) an extension of this work could model in a perceived risk concept within these four risk aspects:

1. *Performance risk* to capture the potential to fail realizing expected advantages.
2. *Financial risk*, which refers to the danger of exceeding targeted budget.
3. *Overall risk* to account for an institutional investor's general risk perception.
4. *Strategic risk*, which is intended to reflect threat to face a lock-in situation, when deciding in favor or against certain trading channels.

The simulation approach for the evaluation of the business value of smart order technology (**Paper 3**) can be extended in two ways: Firstly with an improved dataset, which incorporates order book depth (level two data), the analysis would be alleviated from the concept of partial trade-throughs. This would yield more precise results and simultaneously allow investigations of more routing strategies. The second extension would be to apply the approach used in **Paper 3** on a continuous basis instead of a single snapshot of four weeks. This paves the way to analyze developments within the securities trading value chain over time. In this regard, future research might concentrate on the adoption rate of smart order routers and decreasing rates of trading inefficiencies. Beyond, a continuous approach would provide the basis for event studies on efforts to reduce post-trading costs.

An interesting extension of the analysis of low latency technlogy from **Paper 4** would be a more granular data set. By incorporating anonymized trader identities, the impact of latency can be further illuminated with actual trading strategies in mind. Furthermore, the existence of co-location flags for traders, who exhibit low latency links to the exchange, would allow to better understand how traders with slower connections – being humans or algorithms – and high-frequency traders interact. Furthermore, an extension to other exchanges would increase the ability to generalize already obtained results.

The benchmarking approach for negotiation dark pools presented in **Paper 5** might be extended by additing other alternative trading venues. In this respect the comparison of negotiation dark pools with other important crossing networks such as ITG Posit would shed light on potentially different trading patterns due to differences in market mechanisms. On top, the analysis can be further refined regarding subsequent price reactions at traditional exchanges.

Another interesting research topic might be the smart router concept THOR[29], which was launched by the Royal Bank of Canada Capital in 2011. While in the arms race

[29]A description of THOR's functionality can be found at www.rbccm.com/thor/cid-260178.html.

of high-frequency trading the maxim to act on is becoming faster, THOR is based on distorting trade signals by slowing some of them down, which comparable to a dark pool, makes it harder for high-frequency traders to trade ahead of them. The alternative trading system IEX, which went live on October 25$^{\text{th}}$, 2013 (Picardo 2014), is also inspired by this approach. Besides, few principles, such as no co-location support or high-speed data feeds, IEX introduces a 350 microsecond latency to create a level playing field among its members. While this novation ties together almost all innovations analyzed in this thesis, it would be of great interest to investigate its effects on trading outcomes.

An option for future research beyond the papers submitted for this thesis would be a generalization of the quantitative selection framework by Yang and Jiu (2006). While their framework was initially designed for choosing an appropriate trading algorithm, in the context of decision support systems a generalization could introduce a convenient way to identify potential trading channels for the strategic OCM setup as well as an indication for the most suitable channel for the daily order-by-order operationalization.

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Paper 1

An Order-Channel Management Framework for Institutional Investors

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Abstract

Efficient order-channel management, i.e. the process of information gathering, evaluation, decision and control regarding the setup of the overall trading infrastructure and the actual order routing implementation plays a crucial role for trading success as well as the competitiveness of institutional investors. This article introduces a framework intended to support institutional investors in establishing an individual order-channel management (OCM). For this overall goal, OCM is decomposed into its strategic and operational constituents and the involved key entities, parameters, processes and their interdependencies are outlined. Based on the identified properties, a framework is derived that aims at identifying a suitable mapping from order characteristics to execution venues.

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1 Introduction

Investment decisions of institutional investors i.e. of buy-side[1] companies typically initiate the process of security trading. Within their quest for liquidity it is essential for execution success and the competitiveness of institutional investors to enforce an allocation process that identifies suitable venues as well as execution strategies before orders can be communicated down the value chain. The channeling decision itself is addressed mainly on two levels: First, on a strategic level, a setup for accessing execution venues and building up required infrastructure in terms of people and technology has to be established. Second, on an order-by-order basis, a suitable venue from this pool has to be selected. With new upcoming execution venues in the security trading industry, the demand for order-channeling solutions has intensified (Ramistella 2006). Primarily, the changing intermediation relationships, driven by technical innovations within electronic trading, create new pools of execution opportunities. Thus, institutional investors can choose to execute their orders bilaterally with their brokers at regulated markets, alternative trading systems (e.g. crossing networks) or via new electronic execution concepts like smart order routing, direct market access (DMA) and algorithmic trading. Within this range of execution opportunities the two main entities, execution venues and orders, involved in the process of order-channeling can be described by a bundle of characteristics and interdependencies. Execution venues for instance can be determined by fixed (e.g. market model) and temporary (e.g. market situation and volatility) parameters whereas actual orders typically face a trade-off between urgency and costs. Altogether these bundles of characteristics cause the order-channeling process to become a complex, multidimensional task.

At the same time, new technology-driven solutions enable institutional investors to add value to their order processing and thus offer them the opportunity to outperform competitors. This potential for differentiation receives increased attention with the changes of the European regulation in securities trading. Within these changes that took effect with the implementation of MiFID in November 2007, the topic Best Execution plays a major role as it requires investment firms to set up an individual "Best Execution Policy" and to realize the best possible result for customer orders according to this policy (Gomber and Seitz 2005). The new regulation enables the buy-side to request evidence of best execution.

In order to support institutional investors with the decisions involved in order-channeling, this paper aims at introducing the concept of order-channel management (OCM) and at outlining key parameters for its strategic and operational decisions. Altogether a framework for OCM is set up by identifying and analyzing the key considerations and decision parameters of traders based both on a literature review and an industry screening via interviewing industry representatives. Institutional inves-

[1] Buy-side refers to investment management companies that are "buying" trading services from the sell-side, i.e. investment banks and brokers Harris (2003).

tors can utilize the presented results as a structural approach for implementing their own, individual OCM strategy. To achieve this goal, the remainder of this article is organized as follows: Section 2 presents a brief overview of related work. Based on this, section 3 introduces the concept of OCM by outlining its strategic and operational aspects, their interdependencies, as well as by identifying their key decision parameters. Then, section 4 illustrates the day-to-day handling of operational OCM that maps particular orders to suitable execution venues. Finally, section 5 concludes.

2 Related Work

On a conceptual level, the overall set of available strategic and operational decision parameters for institutional investors and their interdependencies have not been investigated yet. Academic literature focuses on rather specific aspects of the securities trading value chain like *trading styles*, empirical analysis of *markets*, *execution quality* and *order routing decisions*, *market models* as well as *execution costs*:

Behavior of institutional traders, their *trading styles* and related transaction costs are analyzed e.g. in Keim and Madhavan (1997), using proprietary transaction data. There, various hypotheses regarding trading characteristics like the choice of order type, trade duration and immediacy demand are validated. Further, differences between trades initiated by value, index and technical investors are outlined. Focus on informed investors' order types and trading patterns is drawn by Lee et al. (2001, 2004), Anand and Weaver (2004), Anand et al. (2005) and Bloomfield et al. (2005), where evidence for the application of hidden limit orders as well as their performance are presented. The impact of order aggressiveness on execution performance is investigated in Griffths et al. (2000).

Markets and the dimensions of execution quality and costs are addressed by Battalio and Holden (2001). Comparisons of European markets include an analysis of trading costs at the Paris Bourse and London's SEAQ-I (de Jong et al. 1995). Similar comparisons for US markets are provided by Battalio et al. (2000) and Hatch et al. (2001), containing an analysis of market order execution quality (Boehmer 2005) after the introduction of decimals. An overview of the upstairs market for trading of block orders at Paris Bourse is given by Bessembinder and Venkataraman (2004). Altogether an apparent trade-off between costs and execution speed is revealed, emphasizing the demand for models with multiple dimensions of execution quality.

Other investigations address *order flow* and *order routing decisions*. Indications of order flow stickiness to venues despite changes in transaction costs can be found in Ahn et al. (1998). Opportunities to strategically route limit orders to improve execution quality are shown by Battalio et al. (2002). The negative impact of order flow fragmentation on market quality is depicted in Bennett and Wei (2006). Further, a competition for order flow model based on liquidity provision is presented by Parlour and Seppi (2003). These research results outline the importance of non-price dimensions for execution quality.

Beside these findings, related research also focuses on different market models, e.g. the central limit order book (Biais et al. 1995; Grammig et al. 2003), the convergence to order-driven markets in Europe (Demarchi and Foucault 1998) and the relative advantages of floor versus electronic trading systems (Kempf and Korn 1998). Market experiments for a comparison of call markets, continuous auctions and dealer markets are conducted by Theissen (2000). Performance improvement of floor-based trading systems through information sharing among floor brokers can be found in Foucault and Lescourret (2001).

Institutional execution costs across major US exchanges are compared by Jones and Lipson (1999), suggesting that institutions consider characteristics of the used markets. A dynamic model of an order-driven market populated by discretionary liquidity traders that have to trade but can choose their strategy is developed by Foucault et al. (2001). This generates a set of predictions on the relation between market parameters, time to execution and spreads. A model for strategic trading is developed by Hong and Rady (2002), where traders have to learn about liquidity from past prices and trading volume. The model implies that strategic trades and market statistics are path-dependent on past market outcomes. The decision of traders to supply or to demand liquidity in a limit order market is modeled by Hollifield et al. (2002). Simulations of alternative trading strategies based on a detailed data set from a large US investor indicate that the strategy of initially trying to cross all stocks is cost effective (Næs and Skjeltorp 2003). A look at best execution obligations can be found in McCleskey (2004).

Beside these rather singular investigations, the contribution of this article can be compared best to the work of Wagner describing a hierarchy of trading decisions Wagner (2006). The framework derived in this article goes beyond Wagner's operational decision tree model as it creates a generic setup including a strategic level. Another related article that is focused on the operative level is Yang and Jiu (2006) where a quantitative approach for the selection of the most suitable algorithmic trading solution is derived.

3 Introducing the Concept of Order-Channel Management

With the evolution of new execution opportunities, the security trading industry has undergone massive changes in recent years. Order execution transforms itself from a broker intermediated market access to one, which is controlled mainly by electronic means at the buy-side trading desk. Furthermore, new execution venues (e.g. alternative trading systems), trying to meet the requirements of institutional order flow, have been launched. Altogether these changes offer institutional investors potential for cost-savings and improvements in order execution quality.

Definition: Order-Channel Management

Order-channel management *(OCM) is the process of information allocation, evaluation, decision and control of institutional investors concerning the setup of the overall trading infrastructure (strategic OCM) and the actual order routing implementation (operational OCM).*

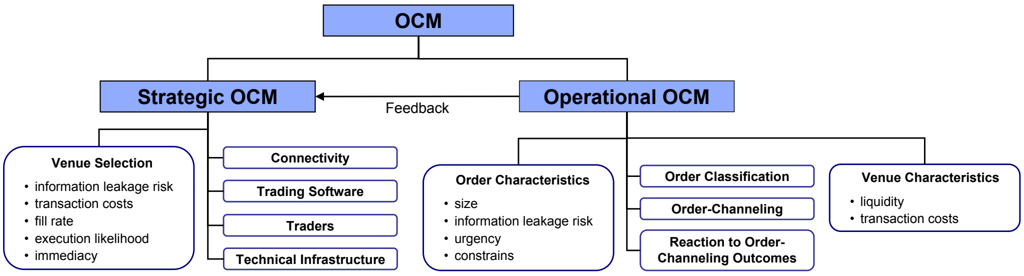

Figure 6: Decomposition of Order-Channel Management Responsibilities

OCM focuses on two interdependent levels that are depicted in figure 6: First, on the strategic level the focus is laid on a pre-selection from a pool of accessible venues. For this purpose, an introspection of the investment strategy is required in order to identify the expected oder flow, which provides the basis for the pre-selection. Further, within the strategic level the required personnel skills of traders, the technical and trading software infrastructure for the usage of new execution concepts like algorithmic trading and the connectivity to sell-side[2] companies and to markets have to be determined and set up. Second, within the environment defined by strategic OCM, on the operational level the actual routing of orders to the pre-selected venues has to be managed on an order-by-order basis. This is established by a comparison of venue characteristics (e.g. liquidity and transaction costs) with actual order parameters (e.g. size, information leakage risk and urgency) as well as execution constraints to be fulfilled. In order to achieve sound routing decisions, an analysis of order characteristic by combining pre- and post-trade analysis shall be incorporated. These two types of analyses provide important feedback information for future adjustments of the decisions within the strategic level.

3.1 Strategic Order-Channel Management

Traditionally, the infrastructure setup of institutional investors for the implementation of their investment decisions refers to their business relationships to brokers. The buy-side traders are responsible for order specifications, order releases to brokers and for phone-based over-the-counter trading, while brokers execute these orders at exchanges or OTC. New execution venues and access channels as well as Information Technology (IT) solutions expand the decision set and thus require a structured approach. Strategic decisions include the overall setup of a trading desk as well as

[2]Sell-side refers to firms that trade for customers and earn money with fees, commissions and research (Harris 2003).

its equipment, technological choices (e.g. usage of DMA or algorithmic trading), relationship management with execution brokers and the selection of execution venues as targets for actual investment decisions. This involves a make-or-buy decision for infrastructure provision and the services necessary to setup execution channels.

Definition: Strategic Order-Channel Management
Strategic Order-Channel Management *(strategic OCM) is the identification, selection and decision for implementation regarding execution venues, their connectivity, trading software, traders as well as the stipulation of technical infrastructure.*

Figure 7 gives an overview of the aspects of strategic OCM that are described in detail in the following sections. Within the considerations of strategic OCM the investment strategy of a buy-side company is an important factor influencing the outcome of trades as well as execution costs (Keim and Madhavan 1997) and thus has to be reflected in the strategic managerial decisions. Therefore, the first step is to determine the expected order flow via analysis of historical order data, interviewing fund managers or an introspection of quantitative investment models. Further, insights to venue performance collected by post-trade analysis give important feedback for the selection of the trading setup and for its evaluation as well as future adjustments.

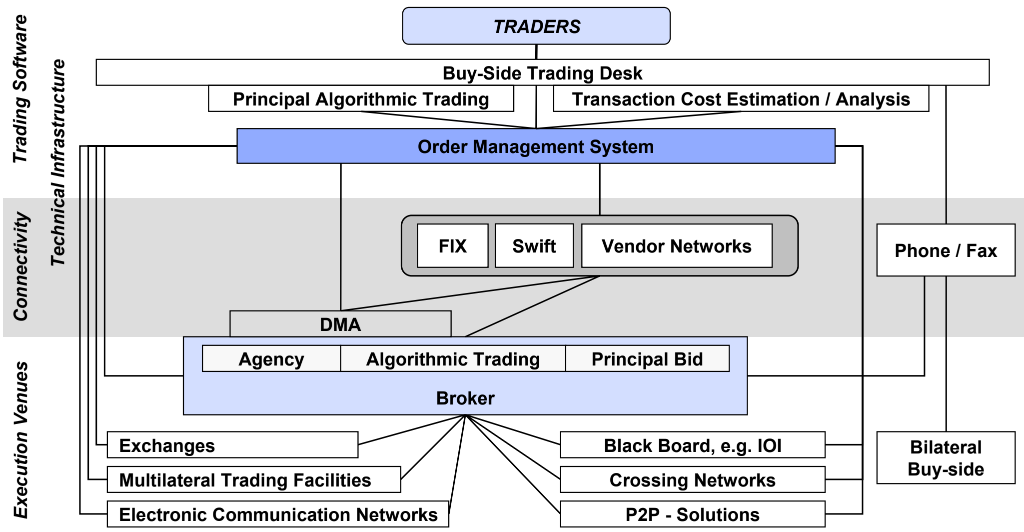

Figure 7: Decision Parameters in Strategic Order Channel Management

3.1.1 Execution Venues

The value propositions of execution venues regarding *information leakage risk*, *transaction costs*, *fill rate*[3], *execution likelihood* and *immediacy* are of high importance for the strategic selection of venues by institutional investors. *Information leakage* risk is addressed by anonymity in one or several phases within a transaction and other functionalities that are offered to camouflage the information provided by order size

[3]Fill rate refers to the amount of purchased (sold) shares in relation to order size (Harris 2003).

(e.g. via iceberg orders) (Chakravarty 2001). Parameters like low fees and commissions as well as a high level of liquidity[4] (O'Hara 1995; Kindermann 2005) decrease *transaction costs* and are therefore an important proposition to reduce the implementation shortfall. Liquidity also influences *fill rates* and the *likelihood of execution* that is tightly related to order routing and counterparty search.

Further, *immediacy* for executable orders is determined by the degree of automatization as well as the access channel, e.g. electronic access to an electronic market enables faster execution. The first traditional channel is direct trading, i.e to trade *bilaterally with another buy-side investor*, which typically involves direct communication between the two trading desks. A drawback of this solution are its search costs within the order routing phase, leading to slow execution and high internal costs of manual processing through negotiation and reconciliation.

Another traditional execution path is the delegation of orders to an agency *broker* who acts on behalf of the investor. The broker chooses a venue that is available to him or identifies trading opportunities with other brokers. An advantage of this channel is the specialization and knowhow of the brokerage company improving fill rate and execution likelihood. Its disadvantage is increased information leakage risk, which is caused by interest conflicts that arise from broker relationships to multiple investors. On top of that, this kind of execution provides lower immediacy because orders are worked successively throughout a trading period.

There exists also the possibility of a *principal bid*, where a sell-side broker guarantees full execution of an order at a given price for a negotiated commission. However, as the commissions or the net price provided by brokers compensates them for taking the position as well as the risk on their books, the transaction costs tend to be higher than those for other channels (Kissell et al. 2003).

To overcome especially the transaction cost issue of these bilateral solutions, buy-side investors can use electronic venues. A first alternative is provided by black board tools, i.e. indication of interest (IOI) messages, which allow to locate counterparties' willingness to trade in a particular stock. However, as IOIs only represent indications rather than executable quotes, likelihood of execution is low. More advanced solutions are crossing networks like Posit, which are able to match large order sizes by applying closed order books and without dismantling the investment interest to other parties. As crossing networks execute orders at the midpoint imported from a reference market and therefore without any market impact, transaction costs are comparably low. Nevertheless, these closed order books have very limited likelihood of execution as well as fill rates. An extension of crossing networks is offered by Liquidnet which searches for liquidity using a peer-to-peer approach. Once the size on the opposite side has been found, both investors are informed and can bilaterally and anonymously negotiate trade price and volume.

[4] Schwartz defines liquidity as the ability to trade whenever one wants to trade (Schwartz and Francioni 2004). A comprehensive overview of liquidity measures can be found in Kindermann (2005).

Further, orders can be executed on exchanges, multilateral trading facilities (MTFs) or electronic communication networks (ECNs). Today's exchanges and MTFs enable electronic access and fast, automated execution. Additionally, these markets offer the possibility to forecast the execution price of orders. Unfortunately, exchanges and MTFs incur higher transaction costs, which attributes especially to market impact and immediacy costs. Therefore, market participants slice their orders over time in order to exploit market resiliency.

Algorithmic trading (Gomber et al. 2005) can be distinguished as another execution venue, which can be developed in-house, bought from a third party or used as a service from a sell-side provider. Finally, the use of sell-side connectivity for direct market access to exchanges while retaining the trading strategies at the buy-side should also be taken into consideration.

3.1.2 Connectivity

Various connectivity options exist that enable institutional investors to place their orders and receive execution confirmations. Some of them are based on industry standards and are independent from actual execution venues whereas others are proprietary to the respective venues. This requires an own infrastructure, causing operational costs, membership fees and data subscriptions. Standardized connectivity solutions are e.g. the Financial eXchange Protocol (FIX) and third party connectivity infrastructure like SWIFT's secure IP network to manage the various channels and to transport orders to various venues. Further, as mentioned before, sell-side connectivity like DMA can be used. These connectivity options can be combined depending on the selected channels.

3.1.3 Trading Software

Trading desks can utilize various software solutions with different features. The basic software are 'plain vanilla' trading screens that are often offered by venues at no additional costs to the access fee. These solutions provide core functions like order entry, receipt of execution status as well as single venue market data. More advanced solutions are order management systems (e.g. Sungard Decalog or Simcorp Dimension), which allow for integrating multiple venues within a single front-end and additionally offer features for inventory management on quantity and value basis as well as reporting functions. Sophisticated software suites include e.g. algorithmic trading engines, pre-trade analysis tools for the prediction of transaction costs, volatility and liquidity development based on historical data as well as tools for position and risk management.

3.1.4 Traders

Even with sophisticated IT support, the need for experienced human traders will prevail. Especially for large orders or orders in illiquid securities human traders provide additional value. This highly skilled type of staff executes strategies for more difficult orders. Additionally, their experience is used to parameterize existing software and to develop new automated strategies. The number and skill level of traders is directly linked to the choice of execution venues, i.e. when DMA or algorithmic trading are used, significantly higher trader skills are required than in case of brokers as primary channels.

3.1.5 Technical Infrastructure

The infrastructure for trading consists of generic information system components. Because the data processed by these systems represents monetary value, these components have to meet high quality standards. Further constraints for infrastructure result from venues which define authorized components (e.g. network components). Additionally, infrastructure has to meet the criteria of scalability, performance, security and reliability. Especially automated venues like algorithmic trading require high computing power to handle real-time market data, which leads to bandwidth requirements in order to ensure real-time data receipt and processing. For example, 1.2 billion trades have been executed over the course of 252 trading days in 2005[5] on one exemplary venue, the New York Stock Exchange, leading to a corresponding number of updates to be processed by the investor's infrastructure, if this venue is used regularly. Thus an infrastructure for multiple venues represents a significant IT investment as well as the corresponding total costs of ownership.

3.2 Operational Order-Channel Management

Based on the setup defined by the strategic OCM process, *operational OCM* provides a framework for the actual order-channeling decision on an order-by-order basis. Therefore, it outlines order characteristics that can be utilized for the identification of suitable venues and access strategies according to the venue characterization outlined in section 3.1.1. Further, it provides important feedback about the performance of each venue that is to be considered in future adjustments of the setup established by strategic OCM. As the individual decisions within operational OCM are supposed to reflect *order constraints*, operational OCM is a constrained optimization process.

Definition: Operational Order-Channel Management
Operational order-channel management *(operational OCM) is the decision process concerning the execution of individual orders reflecting order characteristics, constrains as well as access strategies based on the setup established by strategic OCM.*

For the identification of relevant *order characteristics* the focus is drawn on the investment cycle depicted in figure 8, where an order represents the outcome of an investment decision. Because order execution is supposed to take place at venues which meet specified requirements and at the same time are cost-effective, additional

[5] See statistics at World Federation of Exchanges http://www.world-exchanges.org.

information is required, specifying the actual execution characteristics for each order. Within the investment cycle this information can be provided by a combination of pre-trade analysis concerning the venue accessible from the strategic OCM setup and a post-trade analysis after the completed trade (Kissell et al. 2003).

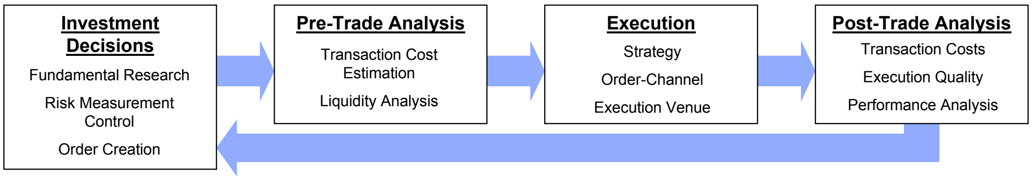

Figure 8: Investment Cycle adopted from Madhavan (2002)

3.2.1 Key Characteristics for Operational Order-Channel Management

As actual transaction costs play a crucial role for execution success, they constitute the starting point for further investigation. These costs are defined as those associated with the implementation of the investment decision (Kissell et al. 2003). They can be further split up into visible costs (e.g. commissions, fees, taxes, spreads) and hidden costs like price appreciation[6], market impact, timing risk and opportunity costs. Hidden costs make the lion share of overall costs, especially when it comes to large orders or block trades (Schwartz and Francioni 2004): First of all, large trades create market pressure and thus lead to market impact e.g. because they sweep the book in an order-driven market. One common technique to avoid this market impact is to slice a large order and to trade more passively over multiple periods (Kissell et al. 2003). This slicing solution leads to other problems. The enlarged trading period leads to timing risk and an increased risk for price appreciation as prices can develop in an unfavorable direction. Furthermore, the motive can become obsolete or, because of information leakage, other market participants might anticipate the order and perform front running. Thus, *order size*, *information leakage risk* and the *level of execution urgency* are the relevant characteristics for operational OCM.

The crucial role of *order size* arises from the fact that market impact costs are a convex function in order size (Bikker et al. 2007). This convexity can be outlined by liquidity measures like the eXchange Liquidity Measure (XLM)[7]. Typically these measures quantify the round trip[8] costs for a specific order size in a security (Gomber et al. 2004). For instance the round trip costs on XETRA for the DAX listed security Deutsche Bank in June 2006 are 1.4bps for a 100k€ order and raise up to 33.3bps for a 2mn€ order[9]. As the assessment of order size depends on the liquidity of the traded instrument, an estimation of the market's ability to execute the desired order

[6]According to Kissell et al. (2003) price appreciation represents the costs of the natural price movement without market impact, i.e. the cost to buy (sell) in a rising (falling) market.
[7]XLM is a trademark of Deutsche Börse Group.
[8]A round trip is a purchase and immediate sale of a particular security or vice versa (Gomber et al. 2004).
[9]Data provided by Deutsche Börse Group.

Order Size	Difficulty Level
0 – 5%	Easy: one day
5 – 15%	Relatively Easy: one day with some work
15 – 25%	Difficult: may require multiple days
25% and more	Very Difficult: recommend multiple days

Table 1: Order Size and Difficulty Level from Kissell et al. (2003)

size with little or no price movement should incorporate market liquidity statistics like XLM mentioned above. Liquidity is also strongly related to market capitalization (Kissell et al. 2003). The most common measure for order size that allows comparisons among different securities is the average daily volume (ADV) (Kissell et al. 2003). Table 1 depicts different size categories as well as their implications for order execution.

Depending on the information other market participants can collect about the order as well as its motivation the risk of front running arises. Hence, the *information leakage risk* is tightly related to the motive of the order. If it is initiated by liquidity motives like cash in and out flows or the requirement to track an index it will face lower information leakage risk. For orders based on private information the situation is contrary. Orders issued by institutional investors rebalancing portfolios accordingly to their research results encounter higher information leakage risk because their private information might be figured out. Thus, informed traders, especiall prominent institutional investors, have to pay appropriate attention to information leakage risk in order to avoid other market participants gaining profits from their trading.

Several studies reveal that institutional investors commonly posses only trading-related reasons for urgent orders, but in fact do not receive immediacy (Schwartz and Steil 2002). For instance Chan and Lakonishok (1995) find out that only about 20% of the value of institutional buy orders are completed within one day, and less than half within four days. Thus, the *level of execution urgency* is also tightly related to information leakage. In this context, most attention is paid to the estimated time that is necessary for the motivation of a trade to become public knowledge (Kissell et al. 2003). Hence trades initiated by transient, private information are executed with higher urgency because this allows exploiting knowledge before it is reflected by market prices. This holds especially for human intermediated markets because of the risk that intermediaries like agency brokers might inform other clients about trading intentions (Schwartz and Francioni 2004). Furthermore, the expected price appreciation has to be considered because it might convey information about the momentum of the security to be traded. Finally, this information can be enriched by statistics for volatility as well as stock classifications like the affiliation to momentum or value growth stocks or the membership to indices that can lead to rapid price movements preceding index reconstructions (Kissell et al. 2003).

Factor	Traders	CIOs
Lowest execution costs	3.53	3.39
Rewarding good research	3.39	3.42
Fastest possible execution	3.37	3.24
Soft commission obligations	2.45	2.44
Portfolio manager direction	2.39	N/A

Scale: 1 (never) to 5 (very frequently, or 75 to 100 percent of the time)

Factor	Weight
Little or no market impact	3.95
Speed	3.42
Not revealing the full size of order to market	3.40
Not revealing the identity of company or fund	3.21
Within the current market inside spread	3.06
Price better than the VWAP	2.93
Low or no commission	1.29

Table 2: On the left key factors determining how institutions choose brokers are highlighted. The table on the right presents factors important to chief investment officers in judging the quality of execution for large orders. Both tables are adopted from Schwartz and Francioni (2004).

The importance of the three order dimensions *order size* for market impact costs, *information leakage* risk as well as *urgency* in form of execution speed are further stressed by the results of a survey by Schwartz and Steil (2002) concerning the assessment of execution quality by chief investment officers, which is depicted on the right of table 2.

3.2.2 Order Classification within Operational Order-Channel Management

With the three classification parameters at hand, we group orders to a total of six classes depicted on the next page in table 3. In a first step small orders are separated because they require less care to prevent market impact. Among these *low touch orders* there is no need for differentiation by information leakage risk because of their low information content. Thus only two further subcategories remain: The first contains *passive low touch orders* with a low level of execution urgency, that can be implemented via liquidity providing means like limit orders. The second class constitutes *active low touch orders* with a higher level of execution urgency, which implies active trading. Among large orders with a low level of execution urgency two additional classes can be specified: Orders with a low leakage risk belong to the class of orders resulting from *strategic trading* like those for share buy-back programs. Orders with higher leakage risk constitute the class of *high touch orders* because they require much attention during their implementation. Finally large orders with a high level of execution urgency can be subdivided into two additional categories: While the parameter setting of high urgency and low leakage risk is reasonably not existent (*not applicable*), orders with a high leakage risk constitute to the class of *urgent high touch orders* being the toughest order type.

Low urgency:

size (small → large) / leakage risk (low → high)	low	high
small	passive low touch order	
large	strategic trading	high touch order

High urgency:

size (small → large) / leakage risk (low → high)	low	high
small	active low touch order	
large	not applicable	urgent high touch order

Table 3: Characterization of orders. On the left the order dimension low urgency is highlighted, whereas on the right the order dimension high urgency is presented.

3.2.3 Order Constrains

Orders might also incorporate constraints which can be constituted already by the order data itself. These constraints narrow the number of possible execution paths or trading venues as wells as the available trading models for a stock. In this context benchmarks like the volume weighted average price (VWAP) or arrival price (AP) are common parameters which are used especially by buy-side companies for an internal execution evaluation or when routing their orders to brokers. Reference prices are also used to measure implementation shortfall (Lehmann 2003), but are not without critique (Schwartz and Wood 2003), especially when the overall market moves in an unfavorable direction. Finally, orders can contain restrictions in form of predefined execution styles (e.g. provided by the portfolio managers of an investment fund company), dependencies on venues and proprietary handling instructions. For example in the left part of table 2 the fact is outlined that traders direct 26% of their orders to brokers as a means of rewarding them for non-trading related services like good research (Schwartz and Steil 2002).

4 Illustration of Actual Order Handling in Operational Order-Channel Management

For the day-to-day handling of operational OCM we propose a subdivision into three phases that are passed by each order. First, *orders have to be classified* according to the three key order characteristics as already depicted in section 3.2.2. Second, the actual *order-channeling decision* has to take place. In the final step order execution should be controlled, which enables *reactions to observed outcomes.*

4.1 Order Classification

The first step is the concrete classification of orders based on the three order characteristics defined in section 3.2.1 and the scheme depicted in section 3.2.2. For this purpose, rules as well as processes should be established that try to achieve a non-overlapping segregation. Here, IT infrastructure plays a crucial role for the processing of market data like daily volumes (e.g. for the comparison of order size to ADV), volatility as well as liquidity which are all required within the order classification.

A tight coordination between fund management and the trading desk enables an integrated optimization of this part of the security value chain and thus helps to achieve higher trading success. First, it increases the traders' insight to the motivation of investment decisions, which helps them to quantify and mitigate the information leakage risk more appropriately. Second, as the emphasis concerning short and long-term alphas becomes available to the trading desk also the determination of the level of execution urgency should improve.

Together with further instructions (e.g. target trading strategies), a pre-trade analysis should be performed and orders are supposed to be mapped to the corresponding classes. During this step, IT-based tools like artificial neural networks might also be incorporated in order to enforce automation in the classification process. Depending on the class, the number of suitable as well as usable venues is narrowed. The final mapping on an order-by-order basis and the 'channeling' is done in the following step.

4.2 Actual Order-Channelling

The actual order-channeling depends on the assignment of individual orders to the order classes. Processing of *large order size* requires usage of multiple liquidity pools. Therefore, state-of-the-art technology allows liquidity consolidation concerning location and time. The former is enabled by advanced smart order routing software seeking hidden liquidity pools (Hallam and Idelson 2003), whereas the latter can be accomplished by manual as well as automated slicing strategies. In this context, Domowitz and Yegerman (2005) have shown that current algorithmic trading solutions are not suitable for all kinds of orders yet, as their investigations have identified a performance breakdown for order sizes above 10% of the ADV .

A common strategy to reduce *information leakage risk* is to hide the complete trading interest or to show only smaller parts. This can be established by using stealth trading techniques that are supported by agency brokers or algorithmic trading. Another applicable technique is to select venues which offer an appropriate value proposition, e.g. pre-trade, trade as well as post-trade anonymity.

Finally, for orders with a *high level of execution urgency* a pre-trade analysis shall be utilized to calculate or at least estimate a trade-off between immediacy and opportunity costs and thus to determine an optimized execution strategy.

Based on these general remarks, we focus on the order/strategy types identified in section 3.2.2. *Passive low touch orders* allow the usage of all venues. To optimize the achieved price and therefore trading revenues, passive strategies via limit orders or venues providing price improvement opportunities might be incorporated. In contrast, *active low touch orders* require a more aggressive execution via market or marketable limit orders[10] on venues offering immediacy. Further, *strategic trading* can also benefit from a passive realization throughout a longer period across several

[10] Buy (sell) order with a limit equal or above (below) the best offer (bid).

venues. As a single release of a *high touch order* would cause a significant market impact, one might initially try to cross them (Næs and Skjeltorp 2003) and if this fails use slicing techniques, splitting the actual order into e.g. hourly or daily packages that can be handled similar to low touch orders. However, an extended execution period bears the risk of opportunity costs and thus has to be continuously tracked. As buy orders tend to convey more information than sell orders (Chan and Lakonishok 1995), their implementation should incorporate additional techniques to reduce information leakage. Finally, for *urgent high touch orders*, constituting the hardest type, automated strategies are not suitable yet. Instead, the full order size or at least large parts of these orders shall be delegated to a broker to whom a trusted relationship has been build up and who either provides a principal bid or who is sophisticated enough to work the order or to "smoke out" desired liquidity via IOIs within the given time frame.

4.3 Reaction to Order-Channeling Outcomes

As, due to their size, orders from institutional investors are far from fire-and-forget tasks *continuous tracking* till their final completion is required. A *readjustment* of a stealth execution strategy becomes necessary when information disseminates or the order cannot be filled. Further, exceptional market changes require also strategy reviews. Under such circumstances brokers typically inform their clients while some automated solutions might fail to achieve this and thus require manual tracking and intervention capabilities.

Beside strategy revisions, order-channeling outcomes should be incorporated in a comprehensive *post-trade analysis* that evaluates execution quality relative to the predefined price benchmarks and adjusts the parameters for the actual strategy selection. Simulations based on historical market data allow to evaluate alternative channels. An example in this context is the Penn-Lehman Automated Trading Project that uses real-time data from US ECNs for the investigation of automated trading strategies (Kearns and Ortiz 2003).

5 Conclusion

For institutional investors, new technology-driven execution opportunities allow for self-directed trading and a greater independence from their brokers, their traditional channels for order execution. Thus, the complexity of their trading desks' tasks and infrastructure increases as they face upcoming execution venues, technology developments as well as new trading strategies. The management of this complexity requires a structured approach.

Our paper extends the existing literature on institutional equity trading by introducing the concept of *order-channel management* (OCM) providing a framework for institutional investors both on a *strategic* and on an *operational level* (section 3). First, strategic OCM addresses management issues regarding execution venues, connectivity, trading software, traders as well as technical infrastructure (section 3.1) and thus provides the framework for operational OCM on an order-by-order basis in daily operations. For the latter we have introduced a classification scheme that maps orders into five classes along the three dimensions of order size, information leakage risk and level of execution urgency (section 3.2). Finally, we have outlined how operational OCM can be implemented within three phases (section 4).

As a future research topic, we will empirically validate our framework – that was derived based on bilateral interviews and industry screening – via a series of structured case studies. Further, we intend to analyze strategic and operational topics like pre- and post-trade analysis for the evaluation of execution quality, especially on multiple venues.

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Paper 2

IT-Driven Execution Opportunities in Securities Trading: Insights into the Innovation Adoption of Institutional Investors

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Abstract

Technological innovations change the intermediation relationships within securities trading. Thus, the question arises which factors drive or hinder their adoption. This paper develops a model to evaluate institutional investors' intentions to adopt the meta-technology we call non-delegated order handling. It focuses on the usage of IT-driven trading systems which enable investors to control the choice of trading venue, order slicing, and timing themselves instead of delegating the execution of stock trading to an intermediary. Therefore the theory of task-technology fit is integrated into the technology acceptance model. Further, it was successfully tested on data from the largest European institutional investors. The results outline that the perceived fit among the system's capabilities and individual trading requirements is the main driver for adoption. Secondly, performance expectations fuel the intention to use trading innovations. Thirdly, for the expected efforts only a weak effect could be shown. Finally, factors like contractual barriers and competitive pressure which investors cannot control do not substantially affect their adoption decision.

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1 Introduction

The evolution of IT enables productivity improvements across multiple disciplines. Thus, explaining IT adoption is an ongoing issue within IS research (Davis 1989; Venkatesh et al. 2003). The focus of this paper relates to the securities trading industry: Here institutional investors like asset management companies or hedge funds traditionally delegate order execution to brokers who act as market intermediaries. The identification of counterparties, the choice of suitable trading venues as well as the execution of their clients' large order volumes without adverse price movements (market impact) are the core competencies of brokers in order execution (Harris 2003). The increasing automatization of securities trading has opened up new IT-based execution opportunities like *direct market access*, *algorithmic trading* and *smart order routing*. Having become popular in the USA, they have come to Europe in recent years (EdHec 2005) and have been altering the traditional value chain:

Direct market access allows market participants remote access to electronic order books without the need for physical presence on exchange floors. That way, institutional investors can forward orders to securities markets directly, without being touched by brokers anymore. Direct market access is offered at considerably lower commissions than traditional brokerage services. Moreover this trading technology provides increased execution speed which allows even taking advantage of short-lived market opportunities. Algorithmic trading and smart order routing are built on the basis of direct market access. Both emulate a broker's activity of placing large orders while minimizing market impact: Algorithmic trading is based on mathematical models exploiting historical and real-time market data to determine how to slice and time orders. It alleviates a trader's work and allows cost savings in comparison to human brokers (Domowitz and Yegerman 2005). Smart order routers perform an automated search for trading opportunities across multiple markets and route suborders to the most appropriate market combination. This helps aggregating fragmented trade intentions (Foucault and Menkveld 2008). The importance of these higher level technologies is shown by (Gsell and Gomber 2009) who highlight the high percentage of order flow originating from automated trading.

New trading technologies facilitate a transformation of order execution from intermediated market access via brokers to self-directed order execution at an institutional investors' trading desk. Thus, the utilization of a package of technologies like direct market access, algorithmic trading and smart order routing is a meta-technology we call *non-delegated order handling* (NDOH).

Beside the potential to save commissions the adoption of NDOH, i.e. the adoption of an appropriate mix of trading technologies, provides the capability to improve different aspects of order execution: Firstly, the ability to react to short-lived market trends is reinforced because responsibility for order execution is not assigned to an external service provider. This satisfies the increasing desire of investment companies to gain control over their trading (EdHec 2005). Secondly, orders can be turned into actual trades immediately. There is no need to route them to a broker's execution desk anymore. For urgent orders based on transient, private information such immediacy is of upmost importance as it helps investors to benefit from their knowledge before it is reflected in market prices (Schwartz and Francioni 2004). Thirdly, institutional investors have to take care of anonymity to avoid other market participants exploiting their trade intentions (Harris 2003). Automated executions help investors to conceal their true trade intentions as algorithms utilize sophisticated slicing techniques. Finally, technology-driven execution opportunities avoid conflicts of interest from broker relationships to multiple investors (Schwartz and Francioni 2004).

Despite these potentials, just more than half the *persons responsible for how to organize the trading process (process owner)* have already adopted such trading technologies in Europe (EdHec 2005). One explanation is that adopting NDOH is not value-creating per se. Instead, it corresponds to an insourcing of the trading task by the means of setting up new trading technologies. Secondly, many institutional investors are engaged in soft commissions (Schwartz and Steil 2002). These are arrangements where brokers provide infrastructure or services free of charge in return for granted order flow. For process owners this constitutes contractual inhibitors as such arrangements oblige them to employ brokers for large parts of their orders. Also the adoption decision requires to assessing whether the capabilities of NDOH are suitable for the characteristics of the trading task at hand. As a considerable proportion of process owners still rely on brokers exclusively our research question is:

> *Which factors influence a process owner's intention to adopt or refuse new technology-driven self-directed execution opportunities?*

The remainder is organized as follows: Section 2 provides a brief overview of related research. Section 3 proposes an integration of the theory of task-technology fit into the technology acceptance model and introduces the hypotheses to be tested. Section 4 describes the employed methodology and data. The empirical results based on perceptions of process owners from the largest European institutional investors are outlined, verified and discussed in section 5. Finally, section 6 concludes.

2 Related Research

From the rich body of IT utilization studies two prominent models have emerged: The technology acceptance model (TAM) and the theory of task-technology fit (TTF).

TAM is a specialization of the theory of reasoned action (TRA) *"to predict information technology acceptance and usage on the job"* (Venkatesh et al. 2003, p. 428). TRA states a behavior mainly determined by intentions to perform it. These intentions arise out of positive or negative attitudes towards the behavior and subjective norms. Norms account for the perception of whether important others believe that the behavior should be performed. In TAM perceived usefulness and ease of use are specified as the two constructs that determine attitude towards a technology. Attitude defines the intention which effects actual IT usage. Further, TAM omits subjective norms as they were not significant (Mathieson 1991). Both, TRA and TAM assume that behavior is volitional. To break this limitation Ajzen (1991) proposed the theory of planned behavior (TPB) as an extension of TRA. TPB includes a perceived behavioral control construct to account for the extent to which users possess control over their behavior. Mathieson (1991) compared TAM and TPB and saw both models work well with slight empirical advantages for TAM. From its initial purpose to analyze the use of IT, TAM has been proven to be applicable for a variety of (acceptance) decisions (Venkatesh and Bala 2008): They include knowledge management systems (Money 2004) and outsourcing (Benamati and Rajkumar 2003). The rationale for outsourcing decisions was the successful application of TRA for technology related decision-making like the acceptance of strategic information systems by senior management (Mykytyn and Harrison 1993). Concerning the role of attitude TAM literature is equivocal. Davis et al. (1989) saw it does not fully mediate the effect of perceived usefulness on intention. Thus, a parsimonious TAM omitting attitude is common in literature, too (Venkatesh et al. 2003). Finally, multiple studies incorporate different constructs as determinants of the TAM core to increase its relevance for practitioners (e.g. Venkatesh and Bala (2008)).

In contrast to TAM, which focuses users' beliefs and attitudes, TTF follows a more rational approach. Dishaw and Strong (1999) underline the shortfall of TAM as it does not consider task characteristics or whether a technology fits the user's tasks requirements. It is addressed by TTF which asserts users adopt IT that fits their needs, i.e. suits their task requirements. Above all users' demands determine the benefits of an innovation (Goodhue and Thompson 1995). To benefit from the overlapping perspectives of TTF and TAM, Dishaw and Strong (1999) have elaborated how these theories can be integrated: They claim the good fit of technology capabilities and task requirements is to reduce effort expectations while increasing performance and actual usage simultaneously. They could successfully employ their model to explain the adoption of maintenance support tools in an organizational context. Nevertheless, they highlight the demand for further empirical validation. An overview of the applicability of TTF is provided by Cane and McCarthy (2009).

Within the domain of securities trading an integrated TAM/TTF model has not been utilized yet. Only the adoption of trading technologies by retail investors and brokerage firms has been analyzed: Lai and Li (2005) apply TAM to investigate the retail adoption of internet banking. TAM is also employed by Lucas and Spitler (2000) to explain the adoption of broker workstations. Although, their results do not support a pure TAM they highlight the importance of job requirements for the adoption decision. Finally, Khalifa and Davison (2006) outline the importance of coercive, mimetic and normative pressures for the adoption of electronic trading systems by brokerage firms.

The contribution of this paper to literature is twofold: Firstly, for all we know this is the first research to investigate factors that facilitate or hinder process owners at institutional investors to adopt NDOH. Such factors are relevant for practitioners, both at institutional investors and brokerage firms, as new trading technologies are currently altering the traditional securities value chain. Secondly, by integrating TAM and TTF the paper at hand aims at exploring the role of those two models in the domain of securities trading. This enables researchers to better understand the similarities and differences in technology adoption across different settings.

3 Research Model

Our analysis accounts for *internal* and *external factors*: Internal factors are defined as those inherently originating from the trading task. They include process owners' assessments how the capabilities of NDOH fit to their trading requirements and their perceptions of NDOH's expected performance and efforts involved with its utilization. External factors are defined as environmental aspects, which cannot be controlled by process owners. In our context they constitute process owners' perceptions of competitive pressure and contractual barriers. The structure of the employed research model, which is based on the conceptualization of Ende and Gsell (2008) is shown in figure 9.

To investigate internal factors, the core of the model is based on an integration of TAM and TTF. TAM has been chosen as its constructs allow assessing the effort and performance expectations of adopting NDOH. Venkatesh et al. (2003) generalize different models to reveal common roots of similar constructs. We adopted their terminology as it is more suitable for our research. Thus the latent variables 'perceived usefulness' and 'perceived ease of use' are termed *'performance expectancy'* and *'effort expectancy'* respectively. Their definitions are generalized, too.

The rationale to integrate TTF is threefold: Firstly, trading is a work-related task for which TTF is said to perform well (Goodhue and Thompson 1995; Cane and McCarthy 2009). Secondly, over 70% of the studies within IS contingency research employ models, which assume that performance will be fostered if the fit among contingency variables increases (Weill and Olson 1989). Hence, a process owner's decision to adopt NDOH has to account for its suitability to the individual trading requirements. Finally, empirical evidence from technology adoption by brokers suggests that a pure TAM might fail and that job requirements should be considered (Lucas and Spitler 2000). Thus, a TTF construct as proposed by Dishaw and Strong (1999) and employed by Klopping and McKinney (2004) for the domain of e-commerce is integrated into our model.

External factors are captured by a generalization of the TAM core towards TRA and TPB: While TAM is an adaptation of TRA, which omits 'subjective norm' (Davis et al. 1989), this construct is reintroduced in our model as subjective norms are expected to be significant in an organizational setting where users may feel social pressure to use IT (Taylor and Todd 1995). To assess the effect of such norms on process owners, the scope of its definition has been broadened to the perception of *'competitive pressure'*. It shall represent the exerted pressures to perform a given behavior by important groups. In the case of NDOH these are the competitors of institutional investors. Further, from TPB we integrate the 'perceived behavioral control' construct. Here this construct is important as process owners might possess no volitional control over adoption. Especially the practice of soft commissions might oblige them to employ brokers for their trading (Schwartz and Steil 2002). Accordingly, the construct 'perceived behavioral control' has been renamed *'contractual inhibitors'* as they might constrain the process owner's ability to decide unbiased about the adoption of NDOH.

The endogenous construct usage (adoption of NDOH) is measured by its frequency and intensity. Frequency reflects the regularity of system usage. Intensity refers to the share of workload. For NDOH, this corresponds to the usage of an own trading desk and by carrying out traditional broker tasks like the search for trade intensions (counterparty or liquidity search). Below, the constructs that account for internal and external factors will be discussed individually.

3.1 Internal Factors

Consistent with existing literature on TAM, TRA and TPB intentions *"...are assumed to capture the motivational factors that influence a behavior; they are indications of how hard people are willing to try, of how much of an effort they are planning to exert, in order to perform the behavior"* (Ajzen 1991, p. 181). In the context of NDOH they reflect the determination of the intention as well as the intended intensity and frequency of NDOH usage. According to Ajzen we hypothesize

> **H_1:** *the intention to use NDOH influences its actual usage positively.*

To form these intentions, the core of our model balances performance with effort expectations similar to the cognitive cost/benefit framework. *Performance expectancy* is defined as the degree to which a process owner expects trading performance to be enhanced by using NDOH. Further, it reflects the extrinsic motivation to actively perform NDOH as *"it is perceived to be instrumental in achieving valued outcomes that are distinct from the [trading] activity itself"* (Venkatesh et al. 2003, p. 448). This can be an improvement of the investment process (preserving portfolio alpha) that has triggered trading. Further, adopting trading technologies might be perceived as a competitive advantage compared to order delegation to brokers. Thus, we hypothesize

> **H_2:** *performance expectancy concerning NDOH influence the intention to use NDOH positively.*

Contrary to the former, effort expectancy is designed to capture the degree of difficulty associated with the adoption of NDOH. Here, two levels are addressed: Implementation complexity accounting for the difficulties to set up NDOH and the complexity which reflects the ongoing effort associated with the usage of NDOH. According to previous research (Davis et al. 1989) we hypothesize that

H_3: *effort expectancy for NDOH is negatively related to its performance expectancy and*

H_4: *effort expectancy for NDOH negatively influences the intention to use NDOH.*

The TTF construct is intended to capture that an increase of fit between the functionalities of NDOH and the requirements of a process owner's trading task is said to improve performance (Goodhue 1995). Unfortunately, little guidance for the application of fit is provided. The difficulty to operationalize fit comes with the fact that items which aim at capturing a broader field of tasks and technologies lose their ability to capture the specific notions of fit (Dishaw and Strong 1998). This deteriorates their explanatory power. Thus, Dishaw and Strong state that *"new measures of fit must be developed for each application to a different task or technology"* (p. 108). Our TTF construct accounts for the degree of fit in respect of trading control. To further appropriately characterize the trading task – execution of orders at favorable conditions – we consider the classification of order difficulty along the three dimensions order size, urgency and information leakage risk (Ende et al. 2007): Large order sizes cause market impact. Urgent orders lead to a similar effect as they try to benefit from short-lived information that enforces to trade immediately. Information leakage risk refers to high anonymity demands. Such orders require to trade large volumes while keeping the overall trade intention secret in order to avoid other market participants taking advantage of it (via e.g. front running). For these requirements of the trading task the compatibility of NDOH is measured. Above, its flexibility concerning variations of these requirements is included. Accordingly to Dishaw and Strong (1999), we hypothesize that

H_5: *task-technology fit of NDOH positively influences its performance expectancy,*

H_6: *task-technology fit of NDOH decreases the effort expectancy for NDOH, and*

H_7: *task-technology fit of NDOH has a positive relationship to the actual usage of NDOH.*

3.2 External Factors

The competitive pressure construct is supposed to account for the fact that the external environment of process owners at institutional investors impacts their decision-making (Goll and Rasheed 1997). As long as an innovation such as NDOH provides competitive advantage literature predicts pressure caused by a competitive environment to positively influence the intention to use it (Jeyaraj et al. 2006). Thus, we hypothesize

H_8: *competitive pressure positively influences the intention to use NDOH.*

Ajzen (1991) states that most behavior depends *"at least to some degree on such non-motivational factors as availability of requisite opportunities and resources"* (p. 182). In the context of NDOH such constraints might be rooted in contractual inhibitors, which prevent process owners from unbiased decisions-making. Empirical evidence for the existence of these constraints and their relevance is provided by e.g. Schwartz and Steil (2002). They identify that 14% of portfolio managers predefine brokers for the majority of their orders. Further, 64% of portfolio managers reward a broker's research or infrastructure provided free of charge by routing their orders to the respective broker. Although such soft commission agreements are used more often in the USA than in Europe (32% to 18% of the traders), this practice constrains process owners in their volitional behavior. Basically it obliges them to use predefined brokers for large parts of their orders exclusively. Therefore, we hypothesize

H_9: *contractual inhibitors exhibit a negative impact on the intention to use NDOH.*

4 Dataset and Methodology

Benefits of NDOH are subject to strong economies of scale. Thus the sample comprises process owners from the largest European institutional investors. Both, process owners who have already adopted NDOH and those who are still considering adoption are included. As NDOH is establishing itself in Europe now (EdHec 2005), an analysis of European institutional investors is performed.

Contact information originates from Thomson ONE Banker Web. To ensure substantial trading activity, only process owners from fund companies have been selected, excluding those from strategic investors and governments. A further restriction to the top 500 in terms of assets under management (AuM) has been performed. The final sample covers 95.4% of the overall AuM in Europe. Each process owner has been contacted by phone personally to request the level of interest. A questionnaire was sent to all those who agreed to participate and could be completed either online or paper-based and returned via mail or fax. Finally, 48 out of 50 responses could be used. As intended this data predominantly represents large institutions for the simple reason that it covers 33% of the total AuM in the original sample. Beyond that the fraction of process owners employing NDOH (60.4%) is consistent with previous descriptive studies (EdHec 2005).

To test the nine hypotheses from above each latent variable in the model (cf. figure 9) is represented by a set of indicators constituting the employed questionnaire (cf.

table 5). These indicators were measured on a fully anchored 7-point Likert scale, ranging from 'completely agree' to 'completely disagree'. To assure that the intended meaning of each construct is reflected (content validity) measures have been adapted from prior empirical studies whenever appropriate or developed during expert interviews. To assure the comprehensiveness and completeness of the questionnaire it was discussed with several industry experts and pre-tested independently later: The pre-tests involved four process owners, respectively two in Germany and two in the UK. Those who employ NDOH for their order handling were interviewed as well as others who still rely on brokers exclusively. The indicators have been modified based on the feedback.

Literature outlines the importance of the right choice for a reflective or formative measurement perspective. A common misspecification results from the *"almost automatic acceptance of reflective indicators"* (Diamantopoulos and Winklhofer 2001, p. 274). To overcome this pitfall, all constructs have been reviewed whether a formative measurement is more appropriate. In the context of this study this is just the case for TTF. For all other constructs a reflective design has been chosen.

As requested by our research model the Partial Least Squares (PLS) approach allows combining both reflective and formative measures (Chin 1998). Thus it has been chosen for the analysis. That way the software SmartPLS by Ringle et al. (2005) has been employed. PLS does not base on presumptions concerning data distribution (Chin 1998). Its requirements concerning measurement scales and sample size are minimal. For a regression heuristic of 10, Chin (1998) suggests a sample size 10 times the greater of *"(a) the block with the largest number of formative indicators (i.e., the largest measurement equation) or (b) the dependent [latent variable] with the largest number of independent [latent variables] impacting it (i.e., largest structural equation)"* (p. 311). For the employed model (cf. figure 9 and table 5) this rule of thumb implies a minimum sample size of 40. Nevertheless there is an ongoing discussion regarding minimum sample size in IS literature. For the interpretation one has to mind the advices given by Goodhue et al. (2006): They conclude that there is no evidence that statistically significant results on small sample are false positives. However for insignificant results their simulations *"clearly suggest that it would be incorrect to assume that the relationships tested do not exist"* (p. 9). Above, one shall be aware PLS might underestimate path coefficients for the present sample size (Hsu et al. 2006). But this does not weaken significant effects identified in this research.

5 Results

5.1 Measurement and Model Validation

5.1.1 Validation of the Reflective Measurement Model

To validate the TAM core, modeled in reflective mode, advices by Chin (1998) have been followed:

A good statistical fit between the indicators and their latent variables (*indicator reliability*) is assured: All indicator loadings to their respective constructs exceed the recommended threshold of 0.707 and are significant at the 0.001 level (cf. table 5 for indicator loadings and *t*-values). For significance tests the PLS bootstrap routine with 500 samples based on the questionnaire data was used. To assess how accurate the latent variables are reflected by their indicators, *construct validity* has to be analyzed. It is composed of *convergent* and *discriminant validity*: Convergent validity measures the internal consistency of indicators assigned to each latent variable. Discriminant validity ensures latent variables to be discriminant from each other. Convergent validity is established as the average variance extracted (AVE), the composite reliability (CR) and Cronbachs's alpha (α) exceed the recommended thresholds of 0.5 for AVE as well as 0.7 for CR and α (Nunally 1978). The respective values are depicted in table 6. Discriminant validity is assured, too: The inter latent variable correlations are lower than the square root of the AVE (see the diagonal of table 5). Further, an analysis of cross-loadings – that are not presented due space limitations – reveals that the loadings of each indicator onto its respective latent variable exceed those to all other constructs.

5.1.2 Validation of the Formative Measurement Model

The following five criteria have been employed to validate the measurement of the formative TTF construct (Chin 1998; Diamantopoulos and Winklhofer 2001):

Firstly, the scope of the latent variable TTF was determined (*content specification*). Depicted in section 3.1 the TTF construct is designed to capture the dimensions of fit concerning trading control, compatibility and flexibility. This definition has been discussed with industry experts intensively.

Secondly, suitable indicators were selected which constitute the construct and cover its scope completely (*indicator specification*). After an intensive literature review, the indicator ttf_1 was chosen for the notion of fit concerning control (cf. table 4). The classification of order difficulty along the three dimensions order size, urgency and information leakage risk has been proposed primarily (cf. section 3.1) for the facets of compatibility and flexibility. Basically large order sizes are a necessary condition for trades to become difficult in terms of urgency or anonymity. Otherwise small (low touch) orders can be executed at exchanges immediately and anonymously. Thus, no indicator was included, which measures fit concerning the requirements for large trade volumes. Empirically this conclusion is also backed up by strong to significant correlations which are exhibited by such an indicator to the other discussed measures. In addition, high urgency demands are theoretically linked with requirements of high trading control. Again, this consideration is supported empirically by significant correlations. But omitting urgency would narrow the employed notion of fit. Different to varying anonymity requirements one might greatly benefit from low urgency as it allows employing slicing techniques or special technology-based trading systems (e.g. crossing networks). Therefore, the perspective of flexibility is chosen for the indicator that captures the fit concerning urgency requirements (ttf_2) whereas the employed fit measure for anonymity (ttf_3) captures the notion of compatibility (cf. table 4). The chosen indicators have been validated during expert interviews.

Thirdly, as the formative measurement model relies on multiple linear regressions strong *indicator collinearity* shall be avoided. Otherwise, they might destabilize results. This issue was reflected although formative indicators are neither expected to covary nor to be independent from each other. Both, a correlation analysis and the inspection of the variance inflation factors (all far below the recommended threshold of 10) indicate no problematic collinearities among indicators.

Fourthly, to assure that the employed indicators are relevant (*indicator reliability*) their signs, weights for the formation of the construct and respective t-values were inspected. All signs comply with the expected effect direction (cf. table 4). Different thresholds for weights exist in literature: Chin (1998) recommends a strict one of 0.2 whereas according to Lohmöller (1989) values above 0.1 are sufficient. The indicator weights for ttf_1 (control) and ttf_3 (anonymity) lie above Chin's recommendation. Only ttf_2 (variation of urgency) is below but at least it exceeds the threshold proposed by Lohmöller. These values are significant for ttf_1, ttf_3 and ttf_2 at the 0.01, 0.05 and 0.1 levels respectively.

Finally, to ensure no relevant aspects of the formative construct were omitted (*external validity*) a reflectively measured phantom construct was used. Diamantopoulos and Winklhofer (2001) claim this can be assumed when the formative latent variable correlates with the phantom construct strongly and significantly. The observed correlations are both strong and significant at the 0.01 level implying that the chosen indicators actually form the TTF construct.

5.1.3 Analysis of the Structural Model

This section analyzes the explanatory and predictive power of the structural model (cf. figure 9) which has been calculated by a path weighting scheme:

R^2 are interpreted identically to those of regression analysis. Accordingly to Chin (1998) the explained variation in usage ($R^2 = 46.4\%$), intention ($R^2 = 58.8\%$) and performance expectancy ($R^2 = 61.2\%$) correspond to moderate levels whereas the R^2 (20.2%) for effort expectancy can be interpreted as a weak level of explanatory power. Three aspects are inspected for the analysis of the predictive power: The

Competitive Pressure (reflective)	**loading**	***t*-value**
In our industry, competitive moves from one firm have noticeable effects on other competing firms and thus incite retaliation and counter moves.	0.918	3.936
In our industry, competition for net performance is highly intense.	0.789	3.601
We feel an increasing pressure concerning net performance.	0.807	3.708

Contractual Inhibitors (reflective)	**loading**	***t*-value**
The financial conditions of the contracts with our broker(s) are too attractive to perform NDOH.	0.868	4.989
By performing NDOH, we could miss valuable additional services provided by our broker(s).	0.787	3.675
By performing NDOH we would lose valuable infrastructure provided by our broker(s) whose replacement cost is so high, that it is not worth the effort.	0.852	4.103
By performing NDOH we would lose valuable research provided by our broker(s) whose replacement cost is so high, that it is not worth the effort.	0.866	4.245

Effort Expectancy (reflective)	**loading**	***t*-value**
Setting up NDOH is so complex, that it is not worth the effort.	0.908	11.122
It takes too long to implement NDOH to make it worth the effort.	0.893	11.350
We find it easy to perform NDOH.*	0.807	8.140

Intention (reflective)	**loading**	***t*-value**
We intend to perform NDOH.	0.970	86.962
We will definitely perform NDOH.	0.978	110.33
We intend to perform NDOH as often as suitable.	0.970	77.574
To the extent possible, we would perform NDOH frequently.	0.988	124.03

Performance Expectancy (reflective)	**loading**	***t*-value**
Our job would be difficult to perform without NDOH.	0.825	13.824
Performing NDOH preserves portfolio alpha.	0.884	18.312
Performing non-delegated order handling increases quality of execution.	0.890	22.869
Performing NDOH gives (will give) us a competitive advantage.	0.841	11.556

Usage (reflective)	**loading**	***t*-value**
We regularly perform NDOH.	0.769	13.504
We use our own trading desk.	0.848	10.413
We perform counterparty or liquidity search ourselves.	0.830	10.032

Task-Technology Fit (formative)		**weight**	***t*-value**
ttf_1:	NDOH satisfies our requirements for more trading control.	0.726	5.872
ttf_2:	NDOH satisfies our requirements concerning varying demands for urgency.	0.159	1.349
ttf_3:	NDOH satisfies our requirements concerning high anonymity demands.	0.300	2.332

*Item has been inverted before it was applied to the measurement model.

Table 4: Indicators and Evaluation Results for the Measurement Model

values of the standardized parameter estimates among the latent variables, their t-values and the effect size (f^2). Path coefficients and their t-values are depicted in figure 9.

Nearly all path coefficients exceed the level of 0.2 recommended by Chin (1998). The only exceptions are those from effort to performance expectancy (H_3) plus to intention (H_4) as well as those from competitive pressure to intention (H_8). H_3 and H_8

	Effort Expectancy	Contractual Inhibitors	Intention	Performance Expectancy	Competitive Pressure	Usage
Effort Expectancy	-0.871					
Contractual Inhibitors	0.273	0.844				
Intention	-0.369	-0.272	0.976			
Performance Expectancy	-0.452	-0.118	0.722	0.860		
Competitive Pressure	-0.030	-0.205	0.139	-0.019	0.840	
Usage	-0.441	0.128	0.595	0.626	0.195	0.817

Table 5: Correlations among Latent Variables and AVE Square Root at Diagonal

	AVE	Composite Reliability	Cronbach's Alpha
Effort Expectancy	0.758	0.904	0.840
Contractual Inhibitors	0.712	0.908	0.880
Intention	0.953	0.988	0.984
Performance Expectancy	0.740	0.919	0.883
Competitive Pressure	0.706	0.877	0.822
Usage	0.667	0.857	0.753

Table 6: AVE, Composite Reliability and Cronbach's Alpha

exceed at least Lohmöller's (1989) minimal level of 0.1. Bootstrapping reveals that all path coefficients from TTF and performance expectancy are highly significant at the 0.01 level. Those from intention, competitive pressure and contractual inhibitors are significant at the 0.05 level whereas H_3 is significant only at the 0.1 level. The inspection of effect sizes shows that the effect of TTF on performance expectancy (H_5) and performance expectancy on intention (H_2) are both strong. All other constructs exhibit weak effects except H_4 which does not necessarily imply meaninglessness accordingly to Cohen (1988). Except H_4, for which no assertion can be made yet, all hypotheses have been proven significantly true.

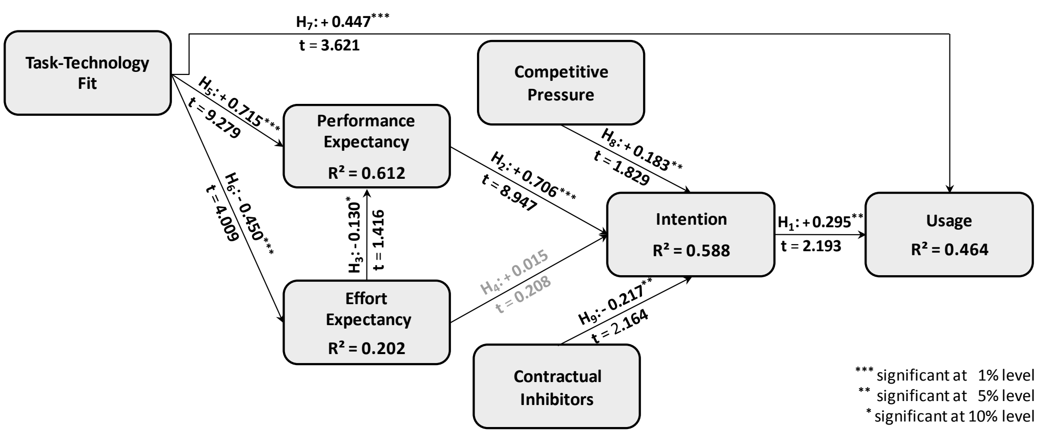

Figure 9: Structural Research Model with Analysis Results

5.2 Discussion

In accordance to TAM literature (Venkatesh et al. 2003) performance expectations are the strongestv predictor for intention in the case of NDOH. Both considered external factors, contractual barriers and competitive pressure, exhibit the expected effects. But their influence on intention is weak. Thus, one can conclude a process owner's intention to adopt technology-driven trading systems is driven by internal factors, i.e. expectations concerning the performance of the trading technology in question.

Aforementioned a significant effect from effort expectancy on intention (H_4) could not be proven although TAM literature claims that it shall exists (e.g. Mathieson et al. (2001)). Following the argumentation in section 4 it would be misleading to conclude this in terms of a contradiction. Two reasons might be assumed: For the largest institutional investors, economies of scale for NDOH are high enough to assess efforts to be negligible. Due to the sample size the effect might not be strong enough for the power of the test to classify it as significant (Goodhue et al. 2006). Further, the impact of TTF goes along with literature (Dishaw and Strong 1999; Klopping and McKinney 2004). But the strong effect of TTF on the core constructs of TAM, performance and effort expectancy was not expected to come along with an equally strong effect on usage. Besides highlighting TTF as a good predictor for performance expectations ($R^2 = 61.2\%$) TAM does not fully mediate its effect on the adoption of new trading technologies, too. Finally, by following the conclusion of Goodhue et al. (2006) conclusion on small samples which suggests restricting the interpretation on significant paths, this research highlights for NDOH that the mode of action for internal factors consists of a strongly significant chain of causations: The starting point is the formation of TTF. This fit determines performance expectancies, which finally define intentions. This phenomenon can be attributed to the strong economies of scale for NDOH. A matter of future research is the effect of effort expectancy. At this point only a weak but significant impact of effort on performance expectations can be shown.

Practitioners should base their decision-making on the fit between the capabilities of NDOH and the requirements of the trading task. Thereby, they shall focus on the ability of new trading technologies to satisfy their requirements for trading control, anonymity and varying urgency demands.

6 Conclusion

Recent technology developments enable institutional investors to perform self-directed trading instead of delegating trading responsibility to brokers, their traditional intermediaries. Thus, new execution opportunities like direct market access, algorithmic trading or smart order routing let those responsible for trading (process owner) reassess intermediation relationships. Although singular (dis)advantages of these innovations have already been outlined in literature, no empirical investigation concerning factors that foster their adoption or refusal is reported yet. To overcome this gap a model has been introduced that integrates TTF into TAM. For external factors like competitive pressure and contractual inhibitors its TAM core has been generalized towards TRA and TPB.

The model has been validated by using the assessment of process owners from the largest European institutional investors. It turns out that internal factors exhibit a chain of strong and significant causations. This chain starts from the TTF construct which is mainly determined by the ability of technologies to provide trading control, anonymity and to satisfy varying urgency demands. TTF affects performance expectations which form the intention to use new trading technologies. It exhibits a strong influence on effort expectations and actual usage, too. Due to the available sample the role of effort expectations remains open for future research. Among external factors both contractual barriers and competitive pressure have weak influence on intention with a light advantage for contractual barriers.

The future research steps are twofold: Firstly, more insights on the role of effort expectancy should be gained. At this point only a significant but rather weak negative impact on performance expectancies could be shown. Secondly, additional variables like risk perceptions might be considered to better explain effort expectations themselves.

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Paper 3

A Methodology to Assess the Benefits of Smart Order Routing

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Abstract

Smart order routing technology promises to improve the efficiency of the securities trading value chain by selecting most favorable execution prices among fragmented markets. To measure the extent of sub-optimal order executions in Europe we develop a simulation framework, which includes explicit costs associated with switching to a different market. By analyzing historical order book data for EURO STOXX 50 securities across ten European electronic markets we highlight an economically relevant potential of smart order routing to improve the trading process on a gross basis. After the inclusion of switching costs (net basis), the realizability of this value potential depends on whether the user can directly access post-trading infrastructure of foreign markets or has to make use of intermediaries' services.

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1 Introduction

In securities trading, different trading intentions are aggregated at exchanges to discover prices. Until the late 1980s, this process has been conducted by direct human interaction at exchange floors. Then, new trading concepts originated from an IT-driven transformation of trading (Schwartz and Francioni 2004). Following Hitt and Brynjolfsson (1996) we measure the potential to generate value of one such IT concept called Smart Order Router (SOR).

The focus of our analysis is the entire *securities trading value chain*. Starting from the investment decision it includes all required stages up to the legal transfer of ownership of traded securities (cf. upper horizontal flow path in figure 10): Trading is a traditionally *intermediated* business (Harris 2003). Thus, *investors* (step 1) communicate their trade interests to human brokers (step 2) who search for counterparties at exchanges to complete *trades* (step 3). Trade confirmations are communicated to post-trading infrastructure providers: In the *clearing stage* (step 4) settlement obligations are determined for each market participant towards all counterparties. That way, clearing provides a risk management function and for efficiency reasons a pooling of multiple trades among counterparties to determine the surplus obligations (netting). *Settlement* (step 5) is *"...the act of crediting and debiting the transferee's and transferor's accounts respectively, with the aim of completing a transaction in securities"* (CESAME 2005, p. 5). It takes place at a Central Securities Depository (CSD). *Custody* (step 6) of shares as well as ownership information is provided by a CSD. For domestic settlement each country typically possesses its own CSD whereas International CSDs (ICSDs) enable access to foreign CSDs for international transactions.

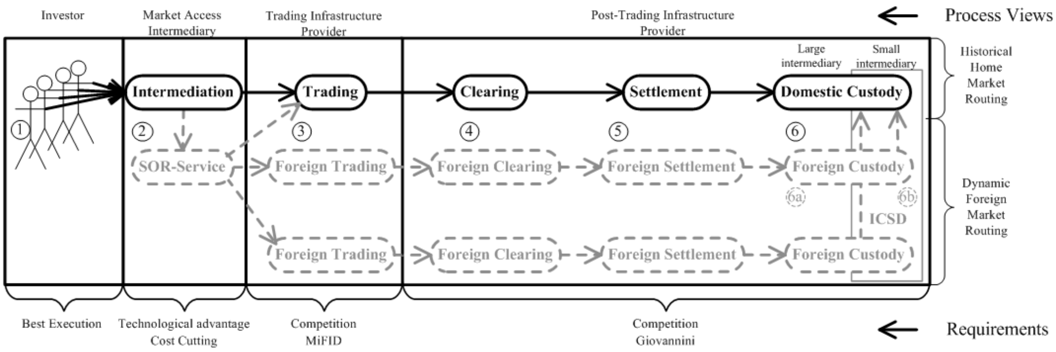

Figure 10: Traditional Securities Value Chain and Changes Induced by a SOR

In the US, alternative trading systems have been introduced at the end of the last century, leading to a fragmentation of markets (Schwartz and Francioni 2004). To enforce best (order) execution, current US regulation (RegNMS) requires mandatory routing of orders from the market initially receiving the order to the one offering the best price. In Europe, no such obligations are in place. Before the Markets in Financial Instrument Directive (MiFID) was introduced in November 2007, stock trading had to take place at national stock exchanges (concentration rule) in various European states. Thus, nearly all trading activity in a security was conducted in its home market (Schwartz and Francioni 2004). To foster competition and to take advantage of technological developments, MiFID abolished these concentration rules. Besides traditional exchanges, this enables the emerge of so-called multilateral trading facilities (MTFs) like Chi-X, BATS or Turquoise. Relevant market share gains of MTFs (Fidessa 2009) in European securities document increasing market fragmentation. To strengthen customer requirements for best execution, MiFID obliges intermediaries to execute customer orders on terms most favorable to the client, i.e. the investor. Within the post-trading stages the European commission aims at fostering competition as it has identified multiple cross-system barriers for cost efficiency (Giovannini Group 2001).

To implement best execution by intermediaries, two alternatives prevail: either to rely on pre-defined static order routing rules, mostly targeting only one market per security (e.g.: the national stock exchange or the respective security's home market) or to employ a dynamic routing by an IT concept called *SOR* (cf. appendix A.2 for a description of a SOR). Gomber et al. (2008) reveal best execution implementations to rely mostly on predefined, static routing rules and only a very low usage of real-time SOR solutions up to now. One reason might be the access to post-trading infrastructures: large institutions apply direct access (cf. step 6a in figure 10 whereas smaller ones require intermediaries to the foreign infrastructure by e.g. ICSDs (cf. step 6b in figure 10) incurring high transfer costs. Therefore, the general question for the business value of SOR arises (Kohli and Grover 2008) and the two related research questions for this paper are:

(1) *Is a static routing process efficient in fragmented European equity markets?*

(2) *Does SOR technology enable for relevant efficiency improvements within the trading process?*

To answer these questions, we develop a general simulation framework for identifying sub-optimal order executions. It can be applied to public data and accounts for explicit costs associated with switching a trade from the original to a different market in European cross-system trading. To infer cost boundaries, two model users are assumed: One user for an intermediated high-cost scenario and another acting in a low-cost scenario with direct access to the respective post-trade infrastructures. Our framework is then validated on a sample of EURO STOXX 50 constituents.

Applied on a continuous basis our framework provides threefold insights: Firstly, intermediaries (brokers and trading desks of institutional investors) can assess the value generation potential of SOR systems on a net basis, i.e. including transaction costs. Secondly, investors can judge the relevance of SOR services for their intermediary choice. Thirdly, regulators can evaluate the effectiveness of the MiFID best execution provisions relative to the RegNMS regime. By comparing the gross (i.e. excluding transaction costs) with the net results the impact of transaction costs, specifically those for clearing and settlement, on the order routing decision is shown.

The remainder of this paper is structured as follows: section 2 reviews related literature, section 3 elaborates on the employed methodology and presents assumptions for the applied transaction cost scenarios. In section 4 the data set is described, followed by our results in section 5. Section 6 concludes.

2 Related Literature

Beside the particular perspective of electronic securities trading, this paper exhibits multiple cross-domain relations in information systems research:

We evaluate the business value of an IT concept with a focus on potential vs. realized value as defined by Chircu and Kauffman (2000). These value categories are used to analyze process-driven and market-driven value flows as well as unrealized value flows caused by barriers and limits affecting these processes. Davern and Kauffman (2000) differentiate between ex ante project selection and ex post investment evaluation in analyzing IT values. The potential value is construed as *"business payoff expected from an ideal technology solution"* (p. 133). As this perspective implies a corporate point of view Mooney et al. (1996) argue to *"move away from firm-level output measures, particularly financial measures, of business value in favour of process-oriented measures"* (p. 77). This is substantiated by the limitation incurred by directly measuring at firm-level (but not at process-level) how and where business value is created by IT.

Weyland and Engiles (2003) highlight the ability of simulations to serve as a basis for business process optimization. Their results are backed by Yen (2008), who illustrate the impact of integrated process optimization for multi-criteria stakeholder process views. Amongst others, direct measurements and computer simulations are described. Energy cost simulations of globally distributed computer centres by Qureshi et al. (2009) prove possible economic gains of smart routing even outside financial markets. Their results outline potential savings of 40% for data centers which dynamically route their workload to regions with low energy costs. For reliable smart routing simulations, Qureshi et al.'s (2009) analysis shows also the demand for a market scope instead of a firm perspective. At firm-level it is impossible to measure process efficiency for the entire market. On top, firms try to conceal their process strategies to retain their comparative advantages.

Regarding SOR technology in particular, Foucault and Menkveld (2008) argue suboptimal trade executions on security markets to be induced by a lack of automated routing decisions. Empirical studies by Prix et al. (2007) as well as Gsell and Gomber (2009) investigate the impact of automated order flow on markets. They underline the high percentage of order flow originating from algorithmic trading. Further, Domowitz and Yegerman (2005) show the business value of algorithms by comparing their overall trading costs with those of human brokers. On top, Bakos et al. (1999) highlight the importance of overall transaction costs.

This paper's contribution to the existing literature is twofold: Firstly, it introduces a potential vs. realized value framework for order routing in fragmented markets. Secondly, to the knowledge of the authors it is the first paper which empirically analyzes the trading process efficiency after the introduction of MiFID. That way, it includes switching costs (i.e. transactions costs), which are relevant for the European case.

3 Methodology and Research Framework

For the empirical analysis of the order execution process, we develop a general simulation framework to calculate the savings per trade (cf. figure 11). As data including individual market participants' identities and cost structures is only available within banks, our framework is specifically designed to employ public market data and fees. It is composed of two main artefacts: a *dynamic SOR engine* and a *static transaction cost modeler*. These are described in more detail below:

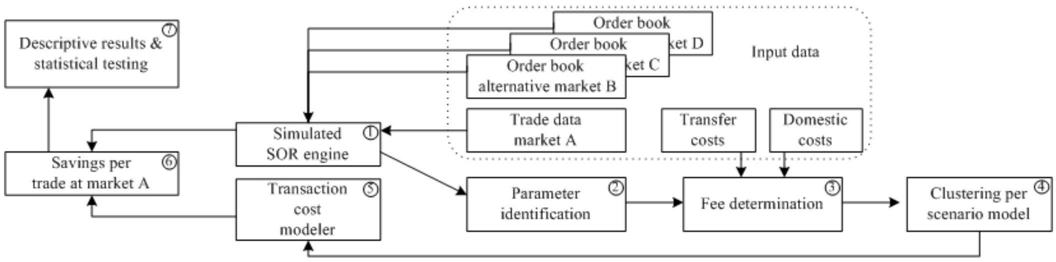

Figure 11: Research Framework Simulating SOR and Modeling Transaction Costs

The SOR engine iterates stepwise through historical trade data, consisting of security names, time stamps, trade price and volume. This data is compared to the historical order book situations of all markets where the trade could have been executed alternatively. According to the information whether a trade could be completed at an alternative market for a better price or not it is classified as executed sub-optimally or optimally respectively (cf. figure 11, step 1 and appendix A.1 for an example).

One might face a situation where some alternative markets offer a better limit price, but with a number of shares insufficient to fully execute the original trade. This kind of sub-optimal execution is sub-classified as *"partial"*. Those sub-optimal executions where the full number of shares might be executed at a better price are labeled as *"full"*. A sub-optimal execution (partial or full) is found if at least one marketplace exists where a strictly positive amount of savings could be realized without considering switching costs. We select the market with the highest potential overall savings for the trade and define the realizable cost difference as *"gross savings"*.

This process improvement information (gross sub-optimal executions) is directed to the transaction cost modeler. This component determines the additional cost to complete the trade at the alternative market. Therefore, cost specific parameters like trade value, security and market characteristics are analyzed, as some markets, feature special fees for foreign stocks (cf. figure 11 step 2). These fees are taken from a database, which consists of costs for trading, clearing and settlement in each respective market (domestic costs) and transfer costs among different CSDs (cf. figure 11 step 3). For reliable results we calculate multiple scenario configurations (cf. figure 11 step 4). As noticed in Giovannini Group (2001) it is not trivial to estimate post-trading process costs for European cross-system trades. This is discussed in more detail in the next sub-section which also elaborates on our specific simulation parameters. With the results from clustering by scenarios, specific transaction costs can be determined (cf. figure 11 step 5). These switching costs are compared to the gross savings generated by using the SOR engine. In the following savings reduced by transaction costs are referred to as "net savings" per trade (cf. figure 11 step 6) which are aggregated in the last step 7.

European Specifics on Transaction Costs in Order Execution

While security markets and respective clearing and settlement providers differ in their cost structures for domestic trading, the main driver of explicit costs is cross-system settlement fees for international, pan-European trades:

Trading and post-trading fees are influenced by various parameters for each provider. Those parameters are partly related to the SOR user's trading characteristics. Other parameters concern the characteristics of a specific trade and the market in which it is executed. To reduce complexity we derive the cost contribution of each process activity as depicted in figure 10. This is consistent with the methodology by Oxera (2007) who models the variable costs directly related to the execution of trades for the required activity and neglects fix costs. Accordingly, total costs of domestic trading in a specific market for an individual trade are defined as:

$$\text{Costs}_{\text{Total}} = \text{Costs}_{\text{Trading}} + \text{Costs}_{\text{Clearing}} + \text{Costs}_{\text{Settlement}}$$

Detailed cost figures and parameters contributing to the calculation of the domestic transaction costs are presented in the appendix A.3.

Cross-system trading refers to situations where an order is executed in a market/country other than the one where the final settlement takes place (i.e. the domestic CSD of the market where the security is primarily listed). In cross-system trading, clearing and settlement, transaction costs depend on the access setup to the respective CSDs. In order to settle a transaction of a particular security, both counterparties must have access to systems enabling them to deliver and receive the security in question. Thus, the distinctive feature of cross-system settlement is how to gain access to a settlement system in another country and/or the interaction of different settlement systems. Giovannini Group (2001) lists five different access setups for a SOR user to a foreign CSD. We select those two which can be identified as a lower and an upper boundary for the relevant switching costs and design two scenarios assuming one specific level of costs consistent for all SOR users in that scenario:

1. **Direct access cost scenario:**
   Here the SOR user has direct (non-intermediated) access to foreign CSDs. This means it has direct access to all facilities – trading, clearing and settlement – necessary along the securities trading value chain. Therefore, the direct access cost scenario obviously represents the lower boundary regarding variable switching costs for individual trades.

2. **Intermediated cost scenario:**
   Here the SOR user depends on intermediaries to access the foreign settlement systems. Among the four potential intermediation services reported by Giovannini Group (2001), our cost analysis identified ICSDs as a realistic upper cost boundary for which price fees are publicly available.

To evaluate whether a sub-optimal execution still holds after the inclusion of switching costs, the fee determination component of our transaction cost modeler artefact delegates the following switching cost information to the scenario clustering component:

For the direct access cost scenario, the switching costs are defined as the difference of the total costs ($\text{Costs}_{\text{Total}}$) for trading, clearing and settlement in the markets, where the trade originally took place to that where it can be executed alternatively. In the intermediated cost scenario this cost difference is extended by additional costs for the transfer of the traded stocks. Thereby it is assumed that the respective securities are kept in the CSD of the alternative market causing costs for a delivery or receive instruction at its CSD and a delivery or receive instruction at the ICSD, i.e. one external instruction to the respective market.

4 Dataset Description and Handling

Our analysis concentrates on actively traded shares on multiple markets in Euro currency. Thus we select the constituents of the Dow Jones EURO STOXX 50 index (as of October 2007). One constituent (ARCELORMITTAL) is not available in the data. Our analysis focuses on simultaneous trading opportunities among multiple markets to be accessible by SORs. This requires markets featuring fully-electronic open central limit order books. In the investigation period, ten European markets are addressed: Bolsa de Madrid, Borsa Italiana Milan, Chi-X, four Euronext (EN) markets (Amsterdam, Brussels, Paris, and Lisbon), NASDAQ OMX Helsinki, SWX Europe and Deutsche Börse Xetra.

For each security/market combination we retrieve trade and order book data from Reuters. It contains each best bid/offer limit and trade prices with respective volume and a date as well as time stamps with a granularity of one second. To determine the order book side of the alternative market to be compared with the original trade price, we refer to the following classification: Trades executed at the best offer are categorised as buy-initiated and those at the best bid limit are said to be sell-initiated. Trades for which a trade direction cannot be determined unambiguously are removed. Moreover, data lacking essential information (e.g. associated volume) are eliminated. As trading hours among the considered ten electronic markets vary slightly, only the periods of simultaneous trading are analyzed. Further, to avoid any bias by strong price movements auctions as well as all trading activity within two minutes around them are removed, such that from a total of 9,163,780 trades, 1,152,875 trades (12.58%) are eliminated.

New limits in a comparison market are considered available when their change arrives within the second of a trade in the original market. Thus they present the most recent order book situation to this trade. With more than one such change within the second of a trade occurrence at one market, the limit resulting in the least savings is taken as a basis for an execution performance comparison in order to retrieve a lower boundary for the improvement potential of the trading process.

Domestic costs for the transaction cost modeler are derived from publicly available data from exchanges, clearing houses and CSDs. Brokerage costs are not included as brokers/trading desks of institutional investors are assumed to constitute the decision point for order routing and consequently their cost structures are taken as the basis of our analysis. The respective transfer costs are derived from the publicly available fee schedules of the two European ICSDs Clearstream Banking Luxembourg and Euroclear Bank (as of late 2007/early 2008).

5 Empirical Results

Our results are based on 8,010,905 trades with a value of 262bn€. They are split into the three cost scenarios: *no cost*, *direct access cost* and *intermediated cost*.

In the no cost scenario, the process optimization potential allows 6.71% of the orders to be better executed with their full size (6.45% of the orders partially). This enables for total savings of 9.50m€ within our sample period, i.e. 7.54bps relative to total sub-optimal execution value and 0.36bps relative to total traded value. The direct access cost scenario exhibits comparable figures. Even in the intermediated cost scenario, assuming explicit transaction costs, which includes the costs for the transfer of securities, 1.41% of orders can be better executed with their full size (1.34% partially). This enables for total savings of 5.90m€, i.e. 10.17bps relative to the total sub-optimal execution value and 0.23bps relative to the total traded value (cf. table 12 in the appendix A.5).

These potential savings outline inefficiencies within the trading process for all three costs scenarios. To validate these descriptive findings, additional statistical tests have been applied (cf. appendix A.4 for details concerning the statistical tests). Table

7 outlines their results in two aggregation perspectives: The *overall perspective* aggregates all sub-optimal executions across all instruments whereas the *security perspective* aggregates individual securities' test results. Checkmarks highlight where savings significantly exceed costs. For the theoretical *no cost scenario* significance can be shown for both perspectives. This is obvious as an idealized SOR is designed to detect saving potentials caused by prevailing market inefficiencies and no switching costs are considered. Thus, when defining best execution as trading at the best available prices our results can be interpreted as significant potential to improve the value chain as far as the trading activity (step 1 – 3 in figure 10).

To have a more comprehensive perspective we have to extend the focus to the complete value chain, i.e. including all activities (step 4 – 6a / 6b in figure 10) and considering all applicable costs. Again, for the direct access cost scenario, significant process improvements can be shown for the entire securities trading value chain. This shows that employing SOR leads to an improved process even when considering costs. Unfortunately, the direct access cost scenario is not applicable for all market participants due to their firm size. Small market participants have to employ an additional intermediary (e.g. ICSD) activity (step 6b in figure 10) providing their access to the alternative markets post-trading infrastructure. Within this intermediated cost scenario results are heterogeneous: Whereas on a security perspective for almost one third (16 out of 49) of the considered instruments the potential for process improvement prevails, in the overall perspective no significance can be shown (red X in table 7). Thus the costs of the additional ICSD activity impede small market participants from taking advantage of the process improvements enabled by SOR.

Cost Scenario	No	Direct Access	Intermediated
Security Perspective	✓	✓	(✓)
Oveall Perspective	✓	✓	✗

Table 7: Potential of SOR to Improve the Efficiency of the Security Trading Value Chain

To highlight an exemplary analysis of this effect for one security, we selected TOTAL as it led the EURO STOXX 50 in terms of market capitalization (as of December 31st, 2007) and as it exhibits most trades and belongs to the stocks with the highest overall traded value. Detailed statistics are shown in table 13 in appendix A.5.

Trade activity varies heavily for TOTAL among market places. As common for most stocks, the primary market exhibits more than ten times higher trade numbers then the second largest. In the no cost scenario for TOTAL, 14.58% or 42,815 out of 293,729 trades at its home market EN Paris could have been executed in their full size at a better price in (at least) one of the other markets. Again, for the direct access cost scenario the figures are comparable (14.51% or 42,608) whereas in the intermediated cost scenario only 2.98% or 8,752 full sub-optimal executions remain.

For the intermediate scenario (cf. table 13 in appendix A.5) we *t*-tested the absolute gross savings (savings of the no cost scenario) against their switching costs. Our findings are heterogeneous among stocks: Since this scenario incurs explicit costs for domestic transactions and securities transfer as described in section 3, the null hypotheses of no systematic absolute savings cannot be statistically rejected for some stocks like TOTAL. Concerning the significance of our results no systematic pattern can be found (cf. table 13 in appendix A.5, intermediated cost scenario, mean costs row). Although EN Bruessel (12.26€) and SWX (165.64€) exhibit the highest gross average savings per sub-optimal execution (table 13 in appendix A.5, no costs scenario section), only EN Brussel's savings remain significant after the inclusion of switching costs (intermediated cost scenario section, mean costs). This is due to EN Bruessel's higher observation number and lower mean switching costs in comprision to SWX Europe and Milan. Regarding the additional intermediary activity (e.g. by an ICSD) this supports the thesis that observable gross average savings per sub-optimal execution (overall more than 0.5m€ for TOTAL) are nullified by high ICSD costs. Accordingly, small intermediaries cannot profit from more efficient trading processes enabled by SOR. An overview for all instruments is provided in appendix A.6.

Altogether, our results show that investors could have realized significant savings on their trades across all instruments. Those savings result from execution conditions superior to those in the market of the actual trade even when considering different levels of explicit transaction costs. Although those savings obviously shrink under the highest assumed transaction costs (intermediated cost scenario), still one out of a hundred trades could have been executed at better conditions.

6 Conclusion

Concerning the addressed research questions our results imply that the current routing implementations in Europe exhibit potential for improvement. Although SOR technology enables for relevant improvements the ability to profit from this potential is limited to large investors since smaller investors face relevant explicit costs in post-trading.

The implications are threefold: Investors should select large market intermediaries enabling them to profit from their potential to provide best execution. Market access intermediaries should use SOR technologies to enable cost savings, comparative advantages and best execution for their customers. European regulators shall enforce initiatives to reduce post-trading costs (e.g. the usage of CSD links) to enable even small market access intermediaries to profit from this optimization potential.

As a future extension of the analysis, inclusion of more detailed data (like order book depth on millisecond basis) will allow to compute the optimization potential by enhancing the partial sub-optimal execution concept. Concerning the data evaluation period, we are implementing a concept which enables us to compute the sub-optimal execution results on a continuous basis. Beyond the snap shot approach taken in this paper, this will provide insights on how the securities trading value chain evolves and allows to assess how market participants adopt SOR technology and how efforts to reduce post-trading costs help to improve the overall efficiency of the trading process.

Appendices

A.1 An Exemplary Sub-Optimal Execution

Our classification of sub-optimal executions resorts to a definition of trade-throughs by Schwartz and Francioni (2004): It states a sub-optimal execution in a particular stock to take place *"...when a transaction occurs at a price that is higher than the best posted offer or lower than the best posted bid and orders at these better prices are not included in the transaction"*. Figure 12 shows an exemplary sub-optimal execution among two markets where the buy order is executed on market A at 86.50€ per share although market B displays a best offer of 86.44€.

Market A

11:36: Buy initiated execution 400 @ 86.50€

→ A sub-optimal execution at market A (trade-through of the better offer limit at market B). This incurs the chance for a price improvement of

Market B

Bid			Offer		
Time	**Quantity**	**Limit**	**Limit**	**Quantity**	**Time**
11:35	343	86,42	86,44	500	11:35
...	...	...	86,50	100	11:35
			...	...	...

Figure 12: Exemplary Sub-Optimal Execution Situation

A.2 Description of a Smart Order Router

The technological foundation of a SOR is the ability for remote access to multiple markets' electronic order books where available trade intentions are displayed (cf. right hand side of figure 13). Connectivity is provided by standardised components such as FIX and third party infrastructure like the SWIFT secure IP network. Based on (1) real-time market data, (2) current trading costs information as well as (3) rules representing client preferences, a SOR performs an automated search for trading opportunities across multiple markets. Herein it aims at splitting an order and routing suborders to the most appropriate market combinations: For an incoming parent order (buy 1,000 shares in figure 13) the SOR determines how it is sliced and how the individual child orders (buy 600 shares at exchange B and 400 at the MTF) are routed to appropriate marketplaces.

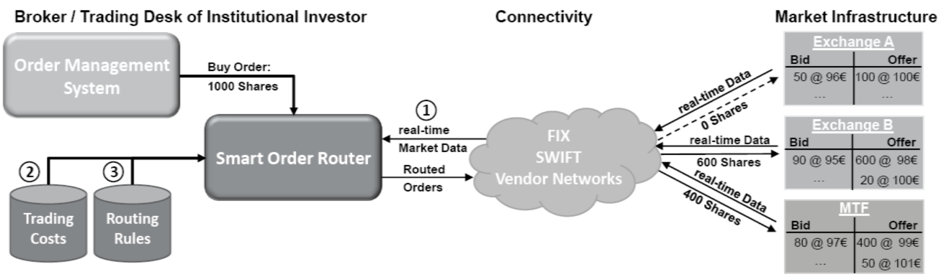

Figure 13: Operating Principle of a SOR Service

A.3 Further Information on Transaction Cost Calculation

Against the background of fee schedules found with European trading, clearing and settlement institutions, the following equations shall provide an overview on the parameter dependencies which have to be considered when determining total transaction costs for domestic trading. It should be noted that not all markets investigated here necessarily apply every component and dependencies differ across institutions. For the trading layer the following equation clarifies this and highlights each component's dependencies in brackets.

$$\begin{aligned} \text{Costs}_{\text{Trading}} &= \text{Transaction Based}_{(\text{Number of Partial Fills, Number of Price Level Hits})} \\ &+ \text{Volume Based}_{(\text{Floor, Cap, Price, Number of Shares})} \\ &- \text{Discount}_{(\text{Total Number of Transactions, Total Traded Value})} \end{aligned}$$

While the dependencies in the transaction based and the volume based component are order-specific, the discount component is based on an investment firm's (SOR user's) trading activity over a certain period of time.

Analogically, next equation reflects the costs and dependencies for the clearing layer.

$$\begin{aligned} \text{Costs}_{\text{Clearing}} &= \text{Transaction Based}_{(\text{Number of Partial Fills, ISIN})} \\ &+ \text{Volume Based}_{(\text{Floor, Cap, Price, Number of Shares})} \\ &- \text{Discount}_{(\text{Total Number of Transactions, Total Traded Value})} \end{aligned}$$

For the costs of domestic settlement equation can be formulated as follows:

$$\begin{aligned} \text{Costs}_{\text{Settlement}} &= \text{Transaction Based}_{(\text{Number of Partial Fills, Netting Efficiency, ISIN})} \\ &+ \text{Volume Based}_{(\text{Floor, Cap, Price, Number of Shares})} \\ &- \text{Discount}_{(\text{Total Number of Transactions, Total Traded Value})} \end{aligned}$$

Therefore, for our analysis we make the assumptions necessary to apply the fee schedules of the trading platforms and fee schedules of providers of central counter party (CCP) clearing and settlement. Moreover, assumptions about how many *partial fills* apply to an order on average are required to allow a price comparison. Some service providers charge fees based on partial fills, others only on the orders sent to the respective service provider. For consistency reasons, the model user is assumed to reach an annual number of orders, which enables to reach the highest discount levels in all of the markets that are analyzed. In particular the markets of Italy and France require considerably high numbers of transactions in order to achieve the highest discount levels. The assumptions concerning partial fills and *price level hits per order in connection with a certain average €-value per order*, are based on numbers provided by Deutsche Börse in an exemplary cost calculation for Xetra (Deutsche Börse AG 2007, p. 1). In that document, Deutsche Börse sets the number of partial fills and the number of price levels hit in a relation to the value of an order posted to its trading platform. This relation has been taken as being linear between the data points provided and used in order to derive the corresponding values for the assumed order size. Although, there is no exact data about the *netting efficiency* achieved by the single European CCPs, Deutsche Börse in a quarterly balance statement published to achieve 90% (Deutsche Börse AG 2003, p. 5). Therefore, a netting efficiency of 90% has been applied for all markets. Our assumptions can be found in table 8.

Annual Number of Orders	7,501,250
Avg. Value per Order [€]	45,000
Partial Fills per Order	2.05
Price Level Hits per Order	2.01
Netting Efficiency [%]	90.00

Table 8: SOR User Assumptions

As the number of partial executions and the average number of price level hits depends on the order size of individual orders, orders with characteristics as given in table 9 are applied for our cost analysis.

Order Value [€]	Average Number of	
	Partial Executions	Price Level Hits
7,500	1.00	1.00
25,000	1.50	1.50
45,000	2.05	2.01
100,000	2.50	2.13
200,000	3.40	2.35

Table 9: SOR User Order Size Assumptions

Applying the above assumptions, the domestic costs per market are based on the respective institutions' publicly available fee schedules and presented in the following table 10. As the fees (non-linear) depend on the executed order sizes we derived typical and relevant order sizes for the fee computation. The figures concerning the sizes of the orders and related characteristics are derived from different sources. First, the order sizes of 25,000, 45,000 and 100,000€ are the same as used in a study by the European Commission on the competition of securities trading and post-trading in Europe (European Commission 2006, p. 28). The order size of 7,500€ per order

	1€	7,500€	25,000€	45,000€	1k€	2k€	1m€
Bolsa de Madrid	1.14	5.78	8.40	10.90	15.20	16.90	16.90
Borsa Italiana Milan	0.34	0.36	0.53	0.70	0.75	0.86	0.86
Chi-X	0.47	0.73	1.35	2.05	3.88	7.20	30.81
EN Amsterdam	1.47	1.47	2.67	3.79	4.90	6.92	8.14
EN Brussels	1.47	1.47	2.67	3.79	4.90	6.92	8.14
EN Lisbon	1.47	1.47	2.67	3.79	4.90	6.92	8.14
EN Paris	1.47	1.47	2.67	3.79	4.90	6.92	8.14
NASDAQ OMX Helsinki	1.05	1.35	2.04	2.83	5.01	8.97	11.05
SWX Europe	0.95	1.32	2.35	3.53	6.72	12.51	38.95
Xetra	1.15	1.15	2.01	3.27	6.74	13.04	24.16

Table 10: Domestic Transaction Costs per Market (Rows) for Respective Order Sizes [€] (Columns)

has been published as average retail order size by an association of German retail banks in the course of its MiFID best execution policy (Deutscher Sparkassen- und Giroverband e.V. 2007). The size of 200,000€ is considered an approximation for a wholesale order size as published by Clearstream Banking Luxembourg (Deutsche Börse Group 2002, p. 19). Finally, the order sizes of one Euro and one million Euros are supposed to provide the lower and upper boundary for the costs. In order to determine the costs for a particular sub-optimal execution of given order size, we interpolate these costs.

Table 11 lists the transfer costs applied in the transaction cost analysis. The respective transfer costs applied for our analysis have been derived from the publicly

	Bolsa de Madrid	Borsa Italiana Milan	Chi-X	EN Amsterdam	EN Brussels	EN Lisbon	EN Paris	NASDAQ OMX Helsinki	SWX Europe	Xetra
Bolsa de Madrid	n/a	25.00	n/a	7.36	7.36	31.40	7.36	27.35	21.95	6.56
Borsa Italiana Milan	29.63	n/a	n/a	7.36	7.36	31.40	7.36	27.35	21.95	6.56
Chi-X	29.63	25.00	n/a	7.36	7.36	31.40	7.36	27.35	21.95	6.56
EN Amsterdam	29.63	25.00	n/a	n/a	7.36	31.40	7.36	27.35	21.95	6.56
EN Brussels	29.63	25.00	n/a	7.36	n/a	31.40	7.36	27.35	21.95	6.56
EN Lisbon	29.63	25.00	n/a	7.36	7.36	n/a	7.36	27.35	21.95	6.56
EN Paris	29.63	25.00	n/a	7.36	7.36	31.40	n/a	27.35	21.95	6.56
NASDAQ OMX Helsinki	29.63	25.00	n/a	7.36	7.36	31.40	7.36	27.35	21.95	6.56
SWX Europe	29.63	25.00	n/a	7.36	7.36	31.40	7.36	27.35	n/a	6.56
Xetra	29.63	25.00	n/a	7.36	7.36	31.40	7.36	27.35	21.95	n/a

Table 11: ICSD Transfer Costs among the Respective Exchanges [€] from Rows (Source) to Columns (Desitnation)

available fee schedules of Clearstream Banking Luxembourg and Euroclear Bank (as of late 2007/early 2008). As both Clearstream Banking Luxembourg and Euroclear Bank provide cross-system settlement services and their charges slightly differ, we consider the least expensive one for each trade in our sample.

A.4 Hypothesis and Statistical Testing

Assuming an efficient trading process, the proportion of sub-optimal executions are expected not to reach a significant level after considering switching costs. To test this hypothesis the means of gross savings are compared with those of switching costs induced by the respective cost scenario. For optimally executed orders (at best market conditions) gross savings equal zero. In the no cost scenario they are strictly positive if a market exists, which offers better execution conditions. After inclusion of explicit trading costs in the other cost scenarios (net) savings can become negative. I.e. if the market offering better conditions incurs higher switching costs, which overcompensate this better execution price.

We have tested the null hypothesis (H_0) below assuming the test statistics to possess a Student's *t*-distribution. Due to varying observation numbers our results are backed by non-parametric tests:

$\mathbf{H_0}$: mean(Savings) $\leq$ mean(Costs)

against

$\mathbf{H_a}$: mean(Savings) $>$ mean(Costs)

A.5 Result Tables

Costs Scenario	No	Direct Access	Intermediated
Number of Trades		8,010,905	
Value [m€]		262,313.9	
Value per Trade [€]		32,75	
Full Trade-Throughs [%]	6.71	6.60	1.41
Partial Trade-Throughs [%]	6.45	5.30	1.34
Savings [€]	9,502,869	9,709,864	5,908,346
Average Savings per Trade-Trhough [€]	9.01	10.21	26.83
Savings per Trade-Through Value [bps]	7.54	7.80	10.17
Savings per Trade Value [bps]	0.36	0.37	0.23

Table 12: Descriptive Statistics of Trade-Throughs for All Instruments

Overview		EN Paris	Chi-X	EN Brussels	Milan	SWX Europe	Overall
Number of Trades		293,729	26,263	465	210	18	320,685
Volume [million shares]		183.14	8.06	0.09	0.03	0.21	191.53
Value [m€]		10,299.57	455.75	4.79	1.72	11.86	10,773.68
Avg. Volume per Trade [shares]		624	307	183	146	11,725	597.2
Avg. Vale per Trade [€]		35,065	17,353	10,295	8,167	658,883	33,595.8
No Cost Scenario		EN Paris	Chi-X	EN Brussels	Milan	SWX Europe	Overall
Full Trade-Throughs [%]		14.58	9.52	53.98	53.33	5.56	14.24
Partial Trade-Throughs [%]		10.88	5.24	4.95	1.90	5.56	10.40
Number of Trade-Throughs		74,778	3,875	274	116	2	79,045
	Full	42,815	2,499	251	112	1	45,678
	Partial	31,963	1,376	23	4	1	33,367
Savings [€]		493,219	16,679	3,360	542	331	514,131
Avg. Savings per TT [€]		6.60	4.30	12.26	4.67	165.64	6.50
Avg. Savings per TT Value [bps]		4.23	3.33	12.73	8.28	51.19	4.22
Avg. Savings per Trade Value [bps]		0.48	0.37	7.02	3.16	0.28	0.48
Direct Access Cost Scenario		EN Paris	Chi-X	EN Brussels	Milan	SWX Europe	Overall
Full Trade-Throughs [%]		14.51	8.06	53.76	35.24	5.56	14.05
Partial Trade-Throughs [%]		9.82	3.16	4.52	0.95	5.56	9.26
Number of Trade-Throughs		71,465	2,946	271	76	2	74,760
	Full	42,608	2,116	250	74	1	45,049
	Partial	28,857	830	21	2	1	29,711
Savings [€]		516,314	13,114	3,429	464	330	533,651
Avg. Savings per TT [€]		7.22	4.45	12.65	6.10	165.20	7.14
Avg. Savings per TT Value [bps]		4.45	2.78	13.05	7.66	51.05	4.41
Avg. Savings per Trade Value [bps]		0.50	0.29	7.16	2.70	0.28	0.50
Intermediated Cost Scenario		EN Paris	Chi-X	EN Brussels	Milan	SWX Europe	Overall
Full Trade-Throughs [%]		2.98	1.07	20.43	1.90	0.00	2.85
Partial Trade-Throughs [%]		2.58	0.61	1.94	0.48	5.56	2.41
Number of Trade-Throughs		16,324	440	104	5	1	16,874
	Full	8,752	280	95	4	0	9,131
	Partial	7,572	160	9	1	1	7,743
Savings [€]		245,661	4,728	2,243	45	287	252,965
Avg. Savings per TT [€]		15.05	10.75	21.57	8.99	287.34	14.99
Avg. Savings per TT Value [bps]		5.01	4.45	12.17	2.67	51.08	5.02
Avg. Savings per Trade Value [bps]		0.24	0.10	4.69	0.26	0.24	0.23
H_0: $\mu(\text{Savings}) \leq \mu(\text{Costs})$	Observations	74,778	3,875	274	116	2	79045
H_a: $\mu(\text{Savings}) > \mu(\text{Costs})$	Mean Costs	7.0837	8.4424	7.1177***	25.910	22.3854	7.1783
	t-Value	-9.9816	-34.17	2.9928	-28.97	0.9923	-14.005

Null hypothesis is rejected at significance level .10 (*), .05 (**) and .01 (***)

Table 13: All Cost Scenarios Results for Total, where TT abbreviates Thrade-Through

A.6 Detailed Results

In the following tables our figures from table 9 will be detailed for the individual EURO STOXX 50 constituents. Table 14 provides the (gross) perspective without the inclusion of explicit trading costs (no cost scenario). Generally, our findings exhibit a high level of heterogeneity among instruments regarding the sub-optimal execution (trade-through) characteristics with the minimum of full sub-optimal execution percentage at 0.16% and the maximum at 16.70%.

Table 15 describes the direct access cost scenario, while table 16 presents the results for the intermediated cost scenario (intermediation by an ICSD). For the later scenario absolute savings obviously decrease relative to those from the gross perspective, as potential savings are reduced and partly even absorbed by the accruing transfer costs. Not so for the direct access scenario, as transfer costs do not accrue and the difference in explicit trading costs between two markets potentially adds to savings if the market providing a price improvement also features lower domestic trading costs.

Instrument	Number of Trades	Value [m€]	Value per Trade [m€]	Full TTs [%]	Partial TTs [%]	Savings [m€]	Average Savings per TT [€]	Average Savings per TT Value [bps]	Average Savings per Trade Value [bps]
Aegon	125,881	2,397.4	19,045	14.30	6.24	287,978	11.14	9.72	1.20
Air Liquide	137,656	1,960.0	14,238	5.21	3.68	18,804	1.54	2.35	0.10
Alcatel-Lucent	117,490	1,730.5	14,729	8.05	6.90	113,667	6.47	14.20	0.66
Allianz	190,387	8,673.0	45,555	13.29	14.34	272,392	5.18	3.50	0.31
Generali	112,315	2,984.2	26,570	0.21	0.11	3,099	8.80	5.64	0.01
Axa	208,272	5,143.0	24,694	11.61	9.73	881,357	19.83	18.71	1.71
BASF	131,899	5,487.2	41,602	7.43	8.24	84,518	4.09	2.81	0.15
Bayer	135,287	5,912.6	43,704	6.19	8.47	112,074	5.65	4.16	0.19
BBVA	137,718	6,415.8	46,587	0.56	0.94	20,345	9.82	10.24	0.03
BCO Santander	165,497	11,024.8	66,616	11.88	22.17	2,034,860	36.11	32.59	1.85
BNP Paribas	297,256	6,746.5	22,696	16.70	12.86	337,179	3.84	3.86	0.50
Carrefour	132,166	2,726.3	20,628	4.07	3.91	22,275	2.11	2.72	0.08
Crédit Agricole	144,184	2,074.5	14,388	3.73	4.66	29,979	2.48	5.59	0.14
Daimler	173,898	8,531.9	49,063	5.94	10.72	170,043	5.87	4.97	0.20
Deutsche Bank	189,235	8,416.7	44,478	11.56	14.13	226,700	4.66	3.20	0.27
Deutsche Börse	96,267	3,532.2	36,691	1.06	2.97	14,754	3.80	4.51	0.04
Deutsche Telekom	103,617	7,702.1	74,332	9.10	7.13	141,996	8.44	5.09	0.18
E.ON	172,070	8,778.9	51,019	8.24	13.48	466,167	12.47	8.38	0.53
Enel	133,043	4,158.2	31,254	1.95	1.61	207,925	43.90	54.79	0.50
Eni	171,544	5,969.3	34,798	0.73	0.56	20,379	9.17	6.36	0.03
Fortis	230,052	5,672.3	24,656	16.51	7.92	488,988	8.70	6.25	0.86
France Télécom	210,668	5,190.2	24,637	6.16	4.55	121,109	5.36	5.43	0.23
GDF Suez	194,471	4,723.2	24,287	8.00	7.06	146,770	5.01	5.14	0.31
Groupe Danone	170,115	3,192.2	18,765	0.39	0.31	21,806	18.28	19.59	0.07
Groupe Société Générale	246,933	6,323.9	25,610	2.01	1.57	161,869	18.32	14.31	0.26
Iberdrola	98,281	4,285.8	43,608	0.16	0.39	8,396	15.49	25.67	0.02
ING Groep	183,835	5,913.2	32,166	3.83	1.76	224,677	21.85	10.60	0.38
Intesa Sanpaolo	119,681	4,805.5	40,153	0.49	0.17	20,275	25.66	11.56	0.04
L'Oréal	137,517	2,327.6	16,926	3.72	4.35	27,480	2.48	4.30	0.12
LVMH Moët Hennessy	150,690	2,710.5	17,987	3.73	4.44	26,264	2.13	3.60	0.10
Münchener Rück	120,327	4,607.9	38,295	9.58	8.82	88,364	3.99	2.64	0.19
Nokia	179,301	9,235.7	51,509	2.39	3.11	167,993	17.05	10.57	0.18
Philips Electronics	202,630	5,368.0	26,492	11.32	6.29	286,566	8.03	5.73	0.53
Renault	171,747	3,104.4	18,075	3.75	4.68	38,316	2.65	4.46	0.12
Repsol	95,611	2,631.3	27,521	0.30	1.05	57,300	44.38	118.40	0.22
RWE	132,587	5,712.3	43,083	5.00	8.56	75,185	4.18	3.99	0.13
Saint-Gobain	158,017	2,521.0	15,954	5.25	5.83	73,193	4.18	7.47	0.29
Sanofi-Aventis	209,655	6,004.3	28,639	6.10	5.22	95,685	4.03	3.46	0.16
SAP	118,283	4,972.4	42,038	4.81	6.23	115,952	8.88	6.51	0.23
Schneider Electric	147,489	2,321.4	15,739	3.84	4.99	24,692	1.90	3.78	0.11
Siemens	190,914	10,639.8	55,731	7.43	11.92	478,100	12.94	8.29	0.45
Telecom Italia	100,334	3,790.0	37,774	0.60	0.80	16,924	12.08	12.75	0.04
Telefónica	171,690	8,535.1	49,712	4.14	8.27	109,178	5.12	7.19	0.13
Total	320,685	10,773.7	33,596	14.24	10.40	514,131	6.50	4.22	0.48
UniCredito Italiano	215,043	11,573.4	53,819	1.29	0.85	110,155	23.98	13.14	0.10
Unilever NV	184,066	4,809.7	26,130	10.33	5.03	260,660	9.22	5.92	0.54
Vinci	193,968	2,890.0	14,899	5.46	3.90	122,639	6.75	12.18	0.42
Vivendi	162,783	3,092.6	18,998	4.87	5.32	67,594	4.08	5.21	0.22
Volkswagen	117,850	4,221.5	35,821	9.02	9.03	86,120	4.05	2.97	0.20
All Instruments	8,010,905	262,313,9	32,745	6.71	6.45	9,502,869	9.01	7.54	0.36

Table 14: No Cost Scenario – Trade-Through (TT) Statistics for All Instruments

Instrument	Number of Trades	Value [m€]	Value per Trade [m€]	Full TTs [%]	Partial TTs [%]	Savings [m€]	Average Savings per TT [€]	Average Savings per TT Value [bps]	Average Savings per Trade Value [bps]
Aegon	125,881	2,397.4	19,045	14.16	5.88	297,277	11.79	10.05	1.24
Air Liquide	137,656	1,960.0	14,238	5.17	2.24	23,684	2.32	3.16	0.12
Alcatel-Lucent	117,490	1,730.5	14,729	8.00	6.13	118,108	7.12	14.80	0.68
Allianz	190,387	8,673.0	45,555	12.74	11.43	278,923	6.06	3.58	0.32
Generali	112,315	2,984.2	26,570	0.17	0.10	2,898	9.57	5.34	0.01
Axa	208,272	5,143.0	24,694	11.41	8.82	887,923	21.07	18.87	1.73
BASF	131,899	5,487.2	41,602	7.30	6.96	87,109	4.63	2.95	0.16
Bayer	135,287	5,912.6	43,704	6.12	7.45	114,547	6.24	4.29	0.19
BBVA	137,718	6,415.8	46,587	0.55	0.92	23,214	11.48	11.72	0.04
BCO Santander	165,497	11,024.8	66,616	11.42	21.96	2,060,041	37.28	33.00	1.87
BNP Paribas	297,256	6,746.5	22,696	16.30	10.63	370,445	4.63	4.32	0.55
Carrefour	132,166	2,726.3	20,628	4.04	2.22	25,576	3.09	3.24	0.09
Crédit Agricole	144,184	2,074.5	14,388	3.72	3.13	32,253	3.27	6.22	0.16
Daimler	173,898	8,531.9	49,063	5.81	7.66	172,350	7.36	5.16	0.20
Deutsche Bank	189,235	8,416.7	44,478	11.22	13.16	233,366	5.06	3.32	0.28
Deutsche Börse	96,267	3,532.2	36,691	1.05	1.67	14,543	5.57	4.62	0.04
Deutsche Telekom	103,617	7,702.1	74,332	8.91	5.43	146,336	9.85	5.26	0.19
E.ON	172,070	8,778.9	51,019	8.04	11.96	466,985	13.57	8.52	0.53
Enel	133,043	4,158.2	31,254	1.71	1.19	203,547	52.80	54.69	0.49
Eni	171,544	5,969.3	34,798	0.64	0.37	18,450	10.68	5.87	0.03
Fortis	230,052	5,672.3	24,656	16.37	6.88	493,020	9.22	6.32	0.87
France Télécom	210,668	5,190.2	24,637	6.10	3.80	120,681	5.78	5.46	0.23
GDF Suez	194,471	4,723.2	24,287	7.96	4.59	145,004	5.94	5.22	0.31
Groupe Danone	170,115	3,192.2	18,765	0.39	0.31	21,462	18.03	19.31	0.07
Groupe Société Générale	246,933	6,323.9	25,610	1.99	1.31	165,841	20.37	14.72	0.26
Iberdrola	98,281	4,285.8	43,608	0.16	0.34	8,330	16.66	25.81	0.02
ING Groep	183,835	5,913.2	32,166	3.80	1.32	228,921	24.29	10.83	0.39
Intesa Sanpaolo	119,681	4,805.5	40,153	0.46	0.17	19,107	25.44	10.90	0.04
L'Oréal	137,517	2,327.6	16,926	3.67	2.61	29,483	3.41	5.28	0.13
LVMH Moët Hennessy	150,690	2,710.5	17,987	3.68	3.07	28,813	2.83	4.32	0.11
Münchener Rück	120,327	4,607.9	38,295	9.38	7.58	94,664	4.64	2.88	0.21
Nokia	179,301	9,235.7	51,509	2.34	2.51	169,307	19.47	10.72	0.18
Philips Electronics	202,630	5,368.0	26,492	11.19	5.65	302,295	8.86	6.07	0.56
Renault	171,747	3,104.4	18,075	3.70	2.81	41,227	3.69	5.32	0.13
Repsol	95,611	2,631.3	27,521	0.30	0.89	57,602	50.44	122.22	0.22
RWE	132,587	5,712.3	43,083	4.87	6.22	76,021	5.17	4.22	0.13
Saint-Gobain	158,017	2,521.0	15,954	5.21	4.25	75,026	5.02	8.17	0.30
Sanofi-Aventis	209,655	6,004.3	28,639	6.04	3.76	103,549	5.04	3.82	0.17
SAP	118,283	4,972.4	42,038	4.75	5.05	116,913	10.08	6.62	0.24
Schneider Electric	147,489	2,321.4	15,739	3.76	3.08	26,252	2.60	4.45	0.11
Siemens	190,914	10,639.8	55,731	7.31	10.17	479,086	14.36	8.40	0.45
Telecom Italia	100,334	3,790.0	37,774	0.50	0.67	15,566	13.29	11.79	0.04
Telefónica	171,690	8,535.1	49,712	3.59	6.16	112,267	6.71	7.46	0.13
Total	320,685	10,773.7	33,596	14.05	9.26	533,651	7.14	4.41	0.50
UniCredito Italiano	215,043	11,573.4	53,819	1.17	0.71	105,221	26.03	12.59	0.09
Unilever NV	184,066	4,809.7	26,130	10.25	4.36	272,291	10.12	6.21	0.57
Vinci	193,968	2,890.0	14,899	5.42	2.94	128,389	7.92	13.07	0.44
Vivendi	162,783	3,092.6	18,998	4.81	3.69	72,510	5.24	5.72	0.23
Volkswagen	117,850	4,221.5	35,821	8.84	7.30	89,792	4.72	3.18	0.21
All Instruments	8,010,905	262,313,9	32,745	6.58	5.29	9,709,864	10.21	7.80	0.37

Table 15: Direct Access Cost Scenario – Trade-Through (TT) Statistics for All Instruments

Instrument	Number of Trades	Value [m€]	Value per Trade [m€]	Full TTs [%]	Partial TTs [%]	Savings [m€]	Average Savings per TT [€]	Average Savings per TT Value [bps]	Average Savings per Trade Value [bps]
Aegon	125,881	2,397.4	19,045	4.36	2.77	150,141	16.73	7.46	0.63
Air Liquide	137,656	1,960.0	14,238	0.23	0.15	4,631	8.85	5.10	0.02
Alcatel-Lucent	117,490	1,730.5	14,729	1.16	0.95	29,178	11.79	7.49	0.17
Allianz	190,387	8,673.0	45,555	1.34	1.61	109,156	19.39	5.33	0.13
Generali	112,315	2,984.2	26,570	0.01	0.00	343	20.16	2.95	0.00
Axa	208,272	5,143.0	24,694	2.62	4.31	624,741	43.28	27.74	1.21
BASF	131,899	5,487.2	41,602	0.81	1.10	32,626	12.96	4.07	0.06
Bayer	135,287	5,912.6	43,704	1.10	1.71	55,292	14.55	5.61	0.09
BBVA	137,718	6,415.8	46,587	0.01	0.02	2,385	53.01	14.48	0.00
BCO Santander	165,497	11,024.8	66,616	2.13	1.53	990,232	163.30	26.58	0.90
BNP Paribas	297,256	6,746.5	22,696	1.53	1.53	337,179	37.10	17.73	0.50
Carrefour	132,166	2,726.3	20,628	0.25	0.22	4,494	7.31	3.66	0.02
Crédit Agricole	144,184	2,074.5	14,388	0.24	0.37	6,008	6.88	6.29	0.03
Daimler	173,898	8,531.9	49,063	1.04	1.67	84,727	17.98	6.69	0.10
Deutsche Bank	189,235	8,416.7	44,478	1.41	2.55	78,684	10.50	3.96	0.09
Deutsche Börse	96,267	3,532.2	36,691	0.19	0.26	5,800	13.49	5.45	0.02
Deutsche Telekom	103,617	7,702.1	74,332	2.47	1.56	83,494	20.01	3.60	0.11
E.ON	172,070	8,778.9	51,019	1.31	4.78	260,995	24.90	13.82	0.30
Enel	133,043	4,158.2	31,254	0.47	0.26	141,548	145.78	79.24	0.34
Eni	171,544	5,969.3	34,798	0.07	0.01	5,841	40.85	5.92	0.01
Fortis	230,052	5,672.3	24,656	3.72	1.73	190,474	15.18	4.33	0.34
France Télécom	210,668	5,190.2	24,637	0.87	0.76	49,628	14.44	5.79	0.10
GDF Suez	194,471	4,723.2	24,287	0.89	0.61	50,650	17.42	5.23	0.11
Groupe Danone	170,115	3,192.2	18,765	0.05	0.04	7,088	47.57	17.28	0.02
Groupe Société Générale	246,933	6,323.9	25,610	0.18	0.28	83,128	73.11	24.89	0.13
Iberdrola	98,281	4,285.8	43,608	0.03	0.02	4,446	88.92	34.15	0.01
ING Groep	183,835	5,913.2	32,166	0.68	0.36	105,026	55.22	12.46	0.18
Intesa Sanpaolo	119,681	4,805.5	40,153	0.15	0.02	8,841	44.88	7.05	0.02
L'Oréal	137,517	2,327.6	16,926	0.14	0.13	5,689	14.82	9.42	0.02
LVMH Moët Hennessy	150,690	2,710.5	17,987	0.15	0.17	5,636	11.53	6.30	0.02
Münchener Rück	120,327	4,607.9	38,295	0.81	1.21	28,057	11.57	4.12	0.06
Nokia	179,301	9,235.7	51,509	0.23	0.15	63,597	92.71	12.73	0.07
Philips Electronics	202,630	5,368.0	26,492	2.10	1.52	135,889	18.49	6.82	0.25
Renault	171,747	3,104.4	18,075	0.29	0.43	16,015	12.99	11.13	0.05
Repsol	95,611	2,631.3	27,521	0.03	0.33	35,350	100.43	414.91	0.13
RWE	132,587	5,712.3	43,083	0.63	1.22	37,790	15.38	7.39	0.07
Saint-Gobain	158,017	2,521.0	15,954	0.41	0.54	25,156	16.92	15.00	0.10
Sanofi-Aventis	209,655	6,004.3	28,639	0.67	0.54	28,691	11.25	3.82	0.05
SAP	118,283	4,972.4	42,038	1.27	1.87	67,303	18.09	7.25	0.14
Schneider Electric	147,489	2,321.4	15,739	0.17	0.20	3,889	7.27	6.00	0.02
Siemens	190,914	10,639.8	55,731	2.04	2.87	285,459	30.50	9.63	0.27
Telecom Italia	100,334	3,790.0	37,774	0.09	0.02	6,052	55.52	8.46	0.02
Telefónica	171,690	8,535.1	49,712	0.16	0.09	19,014	44.22	5.45	0.02
Total	320,685	10,773.7	33,596	2.49	1.95	227,422	15.95	5.01	0.21
UniCredito Italiano	215,043	11,573.4	53,819	0.22	0.08	57,945	88.20	11.59	0.05
Unilever NV	184,066	4,809.7	26,130	1.94	1.15	121,434	21.32	6.42	0.25
Vinci	193,968	2,890.0	14,899	0.42	0.70	58,620	26.96	27.79	0.20
Vivendi	162,783	3,092.6	18,998	0.48	0.63	18,553	10.30	5.47	0.06
Volkswagen	117,850	4,221.5	35,821	0.83	1.09	41,368	18.31	7.07	0.10
All Instruments	8,010,905	262,313,9	32,745	1.01	1.06	4,795,705	28.86	10.15	0.18

Table 16: Intermediated Cost Scenario – Trade-Through (TT) Statistics for All Instruments

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Paper 4

The Impact of a Millisecond: Measuring Latency Effects in Securities Trading

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Abstract

In the course of technological evolution security markets offer low-latency access to their customers. Although latency figures are used as marketing instruments, only little research sheds light on the means of those figures. This paper provides a performance measure on the effect of latency in the context of the competitive advantage of IT. Based on a historical dataset of Deutsche Börse's electronic trading system XETRA an empirical analysis is applied. That way we quantify and qualify the impact of latency from a customer's point of view.

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1 Introduction

Competition among European exchanges has been significantly fueled: In November 2007 the *Markets in Financial Instruments Directive* (MiFID) became effective. With MiFID the European Commission aimed at fostering competition and at increasing transparency in securities trading. Before this date, trading was concentrated at national exchanges in Europe (Schwartz and Francioni 2004), which faced nearly no national competitors.

MiFID enabled the entry of new competitors for traditional exchanges. Increasing trading volumes (Fidessa 2010) of these so called multilateral trading facilities (MTF) force exchange operators to focus more on the needs of their customers (market participants): these are retail and institutional investors. Market operators aim at attracting customers on their trading systems. On top of different pricing schemes they compete through special services such as low latency access. That way they account for the fact that *"[l]atency is one of the major issues in today's trading business"* (Schweickert and Budimir 2009, p. 1).

In general trading can be defined as the act of transferring an investment decisions into actual portfolio positions. Thereby sophisticated trading plans for the slicing and timing of individual orders as well as their precise realization are imperative success factors for exchange customers (Kissell et al. 2003). On the one hand, portfolio turnovers often require the simultaneous coordination of transactions in multiple instruments to minimize implementation risks. On the other hand, execution performance is evaluated by benchmarks based on market prices available at the time of the investment decision or during the time span for entering or closing the targeted position. Thus, a successful market participant (trader) is supposed to *"sense a market, spot pricing discrepancies, and make lightning-fast decisions"* (Schwartz and Francioni 2004, p. 60).

Concerning these requirements for fast reactions, market setups based solely on manual trading floors are restricted mainly by human traders' limited capacity of reaction and perception. For such markets latencies, i.e. the time which elapses from the emergence of a new trade opportunity and the actual order arrival at the market, correspond to multiple seconds. The reduction of this time period by employing IT is said to exhibit positive effects already since the 1980s (Easley et al. 2014).

Among other efficiency improvements triggered by IT the most notable has been the shift from floor trading to electronic trading systems (Kempf and Korn 1998; Theissen 2000). The electronification of market venues in Europe, i.e. exchange trading systems like XETRA (Deutsche Börse), SETS (London Stock Exchange) or NSC (Euronext France) took place in the late 1990s and enabled market participants to access electronic order books[1] via remote access without the need for physical presence on an exchange floor (Schwartz and Francioni 2004). This so called *direct market access*

[1] A list of buy and sell orders for a specific instrument sorted by price/time priority. Each update might change its structure, i.e. the included price limits and their respective volumes.

Market Place	Average Latency [ms]
Chi-X Europe	0.4 (co-located)
London Stock Exchange	< 6
Euronext	13
Deutsche Boörse	37
OMX	43

Table 17: Latencies for Direct Market Assess from Chi-X Europe (2010)

allows straight through processing for accessing securities markets which reduces the necessity of media breaks and manual human interventions (Weitzel et al. 2003). Beyond these benefits it enables algorithmic trading engines which simulate order placing strategies of human traders to enter or close portfolio positions. A typical example is to reach the volume weighted average price (VWAP) when buying or selling an instrument.

Deutsche Börse reports 45% of transactions on XETRA to originate from algorithms in Q1/2009 and to be still increasing (Deutsche Börse AG 2009). The rational for the success of algorithmic trading is plentiful: Firstly, algorithms allow overall cost savings in comparison to human brokers (Domowitz and Yegerman 2005). Secondly, they break human limitations and thus allow permanent surveillance of outstanding orders. This capability allows algorithms to readjust their trading decisions *immediately* to changing market conditions – i.e. retain their unexecuted orders at best market prices (top of the book) (Gsell and Gomber 2009). Besides, algorithms have been proven to substantially improve market liquidity (Hendershott et al. 2011). I.e. they post passive limit orders and thus provide trade opportunities to potential counterparties in times when they are scarce.

Institutional investors, which generate most trading volume (Schwartz and Francioni 2004), exhibit an increasing need for algorithmic trading. Therefore, their trading needs became the focus of market operators, which have entered an arms race for low latencies (Grob 2010). Typically they offer so called co-location or proximity services: here the latency to send orders from the clients' office location is eliminated by hosting these clients' trading algorithms on servers nearby the marketplace's system. Table 17 depicts exemplary latencies from October 2008 used in promotion by the MTF Chi-X Europe.

Additional to algorithmic trading, which is designed to enter or close stock position based on the decisions from portfolio management, the electronification of trading paved the way for another kind of quantitative trading strategy (Aldridge 2010): so called *high-frequency traders* (HFT) basically aim at taking advantage from short-timed market inefficiencies. In this respect HFT trades are triggered by computer systems as immediate reactions to changing market conditions. That way they perform a vast number of trades with relatively low profits. The price discrepancies HFT strategies are based on are only restricted to leave a gain over after trading costs.

According to Narang (2010) HFT margins in the US are as low as 0.1 cent per share (cps) after trading costs while typical brokerage services amount to 1–5cps. Another distinctive feature of the high monetary turnovers of HFTs is their short position holding times: typically not more than hours or even just seconds. On top, overnight positions are avoided. A typical evolution of the cumulated inventory changes of a HFT acting as a market-maker or middleman at the MTF Chi-X Europe as well as Euronext simultaneously is depicted in figure 14. Similar to a classical money changer market-making is designed to earn the price difference from buy (bid) and sell (ask) price differences. Therefore, a HFT following a market-making strategy will try to have a limit at the best prevailing prices on both sides of the order book.

Altogether HFT strategies have become a billion-dollar industry: In the US they account for more than 60% of the average daily volume in equities trading (Aite Group 2009). Although still entering the European market, HFT strategies are already involved in one out of four trades there and are expected to reach 45% in 2012 (Cave 2010).

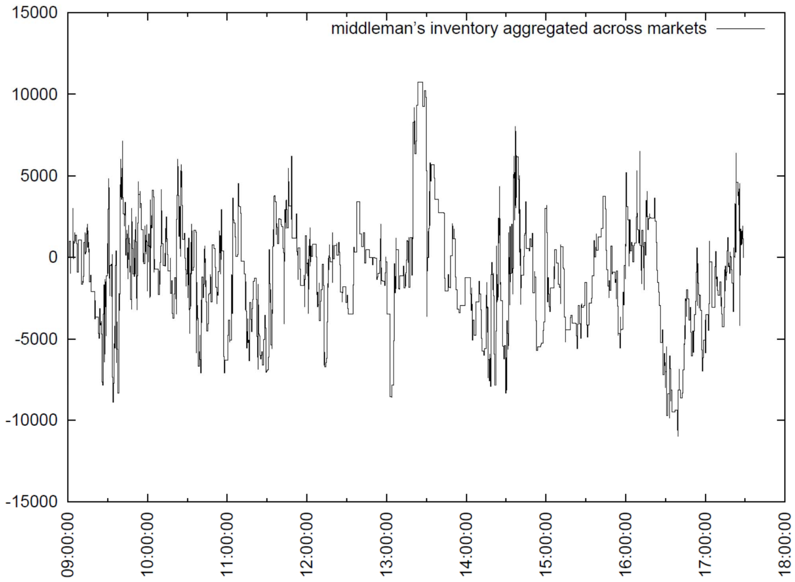

Figure 14: Inventory Evolution of a Market-Maker from Jovanovic and Menkveld (2011)

As trading is a zero-sum game profits of HFT traders correspond directly to losses of other market participants. Basically if some participants are able to react quicker to new information they can exploit limit orders of slower market participants as a kind of free trading option (Riordan and Storkenmaier 2012). From an IT business evaluation perspective therefore the following two research questions arises (Clemons 1991):

1. *What are effects of latency?*
2. *Do they require market participants to employ low latency technology?*

To provide market participants guidance in answering these strategy dependant questions, we develop a performance metric to measure the impact of latency consistently among different combinations of markets and instruments. The paper proceeds as follows: Section 2 presents a literature review. The research methodology is introduced in section 3 before section 4 describes the employed dataset. Our results are depicted in section 5 and discussed in the following section 6. Finally, section 7 summarizes and concludes.

2 Related Literature

Our research – the investigation of the impact of latency on securities trading – is related to two different disciplines: research on (i) *the general value of IT* and (ii) *literature dealing with latency in the security trading domain.*

Due to the complexity in IT valuation research different attitudes on the economic impact of IT have been discussed (Kohli and Grover 2008): One major research stream takes the perspective of sustainable competitive advantage for which IT is seen as a key resource (Brynjolfsson and Hitt 1996). At least IT investments are valued as strategic options to safeguard from potential future losses (Clemons 1991). Nevertheless, IT-created value manifests itself in many ways (Kohli and Grover 2008), which might be intangible (Bharadwaj et al. 1999). In the case of latency reduction technologies such intangible dimensions might be an improvement of execution quality in terms of a higher precision concerning the realization of targeted positions. Thus, our research focuses on the probability of relevant order book changes that occur before an order arrives at the market and the relation of this probability to different latency levels as well as time periods within a trading day. This constitutes a performance metric for latency.

Melville et al. (2004) propose that *"[t]he greater the degree of competition in an industry, the greater the extent to which firms achieve efficiencygains via IT"* (p. 306). Electronic securities markets exhibit a highly competitive character and an ongoing arms race of IT. In this respect our performance metric contributes particularly to this proposition, i.e. to which extent investments in IT in this field may yield competitive advantages.

Schryen (2010) states process performance to be related to business performance from various IS perspectives. Customers in our case, which are primarily institutional investors such as banks, exhibit tendencies for standardization, automation and flexibilization of IT and the supporting processes (Braunwarth et al. 2010). In case of the order submissions process our performance metric helps to assess the effects of automation. Weitzel et al. (2003) argue that banks can yield high internal straight through processing rates, which implies the necessity of low error rates in our context, by consistent integration of all systems involved in the trading process.

Within the domain of securities trading, related literature like Easley et al. (2014) investigate the impact of latency reductions on market quality criteria like liquidity[2] by the introduction of IT. That way Easley et al. (2014) analyze the improved information disintermediation for off-floor traders from two minutes to 20 seconds at the New York Stock Exchange (NYSE) in the 1980s. Their results predict a positive effect on liquidity. Nevertheless, these results should be interpreted with care as they might be affected by other market structure changes during the investigation period. Current technology allows latencies of millisecond or sub-millisecond magnitudes. Thus, different measurement starting and end points might distort results as pointed out by Schweickert and Budimir (2009). To overcome this problem they propose a standard benchmark methodology based on order action round trip times: It is defined as the time span from the order action initiation (i.e. order submission) and trading system response (i.e. execution confirmation) at the customer's market access point. This notion is similar to our definition of latency. Further, they analyze the properties of latency based on data from Deutsche Börse's XETRA trading system in 2007. That way three drivers for latency are identified: trading activity, time of day as well as the distance between customer access- and market operator host computer. Latency exhibits different levels with a similar structure for every trading day (day pattern). Basically latency increases during the day due to rising trading activity. On top, a remarkable latency peak can be observed at releases of US economic data. The mean latency is reported to amount to 51.9ms with a standard deviation of 25.2ms. Their numbers provide a range of latencies for our analysis setup. More recent empirical work on the effects of latency on market quality measures are Hendershott and Moulton (2007) and Riordan and Storkenmaier (2012). Unfortunately, their results are ambiguous: Hendershott and Moulton (2007) find that the latency reductions by the NYSE Hybrid upgrade cause a decrease of liquidity. In contrast, the results of Riordan and Storkenmaier (2012) show positive effects for a Deutsche Börse system upgrade on April 23rd, 2007, which decreases the system's roundtrip time from 50ms down to 10ms.

Modeling the costs of latency, the working paper of Moallemi and Saglam (2010) is also related to our work. In a highly stylized model the development of the costs of latency in US securities markets from 1995–2005 is examined. Costs in this model only arise from limit changes whereas our perception of order book fluctuations includes limit and volume alterations. Several assumptions of the study seem critical in face of our results. Especially, a constant arrival rate of impatient buyers and sellers seems unlikely considering the day patterns of order book fluctuation. However, findings such as the concave effect of latency on costs are congruent with our findings.

In the field of IS literature our study contributes to the research as it provides a performance measure on the effect of latency in the context of the competitive ad-

[2]A simplistic definition of liquidity is the ability of a stock position to be established or unwind quickly without or only minimal negative price movement despite its actual size (Schwartz and Francioni 2004).

vantage of IT. Regarding the domain of securities trading we introduce the notion of order book fluctuation as the key variable, which determines the latency impact. This differs from trading activity and volatility as these do not incorporate volume changes. Because algorithms tend to rapidly place and cancel limit orders neither trading activity nor volatility is affected. Whereas order book fluctuation does increase and latency issues arise.

3 Methodology

3.1 Modeling the Impact of Latency

While conceptions of latency differ not only among research fields but even within a research area an approach to assign economic value to latency can only be undertaken with respect to the specific business (equity trading in our case) that depends on latency. As described before the need for speed in today's marketplaces raises the question who actually demands the low latency connections and what is the economic driver behind this.

To our best knowledge so far no concept has been developed that attempts to assign meaningful economic numbers (amount of cash) to latency in this context. The phenomenon that high speed accesses seem to be utterly indispensible for some trading strategies raises the question about the effects for other traders without such an access. Following the argumentation of Brynjolfsson and Hitt (1996) *"...a firm with a unique access to IT may be in a position to earn higher profits from that access"* (p. 124), it might well be the case that HFT is an example of such a unique access. While not only the low latency connection but also the developed algorithms to exploit them would define this unique access to IT.

The following paragraphs will describe a method, which aims at connecting latency to expected untruthfulness of information and deduce a metric to account for this information unreliability. In this respect differing concepts will be examined. However, the basic idea behind them is the same. Every trader, human or algorithmic, depends on latency. When submitting an order at t_1, a decision has to be made about order size and volume based on information (usually the order book, describing current bids and offers at the market) generated at time t_0. When the order reaches the market at time t_2 the situation at the market might again have changed (cf. figure 15).

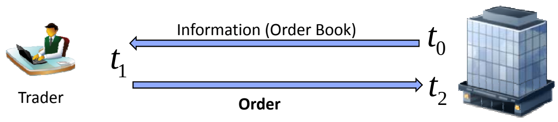

Figure 15: General Dependence of a Trader on Latency

Our concepts all make use of this fact. Just based on latency figures alone no definitive predictions of the amount as to which the situation might differ between t_0 and t_2 can be made. Thus, it is impossible to conclude from a given latency whether the inherent risk of meanwhile market changes is small or large.

Since the amount of changes and the impact on ones strategy are unknown it is only possible to estimate the outcomes of the gamble, which is caused by the latency lag. In the following subsections we present ideas how this can be done.

3.2 Order Book Fluctuations

Taking a closer look at the demanders of low latency trading connections exhibits that most orders of algorithmic trading especially high-frequency trading concerns only the top of the order book (Gsell and Gomber 2009). Most orders issued by algorithms exactly match the best ask/bid price and volume and if no execution takes place orders are canceled immediately. Therefore, we introduce the notion of *order book fluctuation*, which we define as the probability of a change in either the best ask or bid limit or the corresponding volumes at the top of the order book. Formally, we define $p_{fluc}(x)$ as the probability of such a change in x milliseconds. This is of course a fundamentally different approach than to concentrate on volatility because order book fluctuations can occur without price changes.

For the case that no information about trading intentions is available, we cannot distinguish whether they are favorable or unfavorable. Thus, in this situation we regard any change in the order book as possibly negative. In the progress of this paper we refine this measure to 4 fundamental trading strategies, where only specific changes are regarded to be relevant.

3.2.1 Global Order Book Fluctuation

As described before, without any knowledge about a strategy, any change in the order book may have negative consequences, which a trader could not predict when he submitted the order. An infrastructure provider of data warehouses for traders for example has to decide where to place his facilities in order to meet his customer's demands and she certainly has no information of the different trading strategies it will be used for.

Thus in this case, for a given latency x, the probability of a change of the order book within this time, is the probability that either the limits or the volume has changed without taking care of the direction of that change.

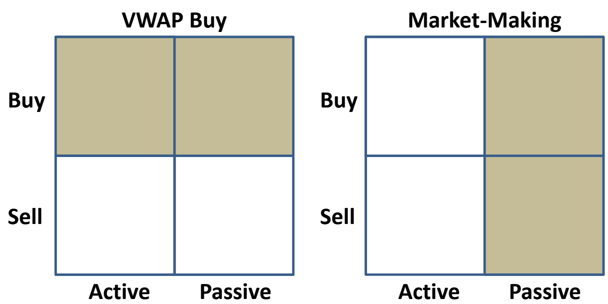

Figure 16: Characteristics of Typical Trading Strategies

The following paragraphs will define relevant changes for four basic strategies. These cases are chosen rather for demonstration purposes of the methodology than to simulate a real application on a complex algorithm. However, every strategy is a combination of those four basic strategies. The institutional investor's VWAP buy strategy and a market-making strategy are stretched out in different directions regarding the basic components as figure 16 depicts.

The differentiation between active and passive strategies refers to the application of marketable and non-marketable orders respectively. This is explained in more detail in the following subsections.

3.2.2 Active Strategies: Buy Active, Sell Active

We define active strategies as strategies that only uses market orders, i.e. orders that are executed immediately at the best currently available price in the order book. These orders are always executed, whenever a corresponding counterpart exists in the order book.

Thus *Buy Active* is a strategy, where a trader, who wants to build up a position, simply submits market buy orders. After the submission order book changes can occur that may lead to an unfavorable result. It can happen that the best available offers at the time of the order submission are already taken either partly or completely cleared by the time the order reaches the book. If they are taken partially the order is filled only partially at the expected price. Then we could observe a decrease in the volume at the top level in the order book at the time the order reaches the order book. If at the time of the order arrival the ask limit has increased, i.e. the orders were cleared completely, the full order will be executed at a higher price. Accordingly, relevant unfavorable order book changes are ask volume decreases and ask limit decreases.

Analogously, for a *Sell Active* strategy undesirable events at the bid side of the order book are of the same type. Volume decreases may lead to partial executions and inferior prices. Only here of course bid limit decreases are considered negative since the seller receives a lower price.

3.2.3 Passive Strategies: Buy Passive, Sell Passive

Passive strategies are those which only apply non marketable limit orders. A typical example could be that of a market-maker who, like a classical money changer, makes profits by spread earnings from simultaneously buying and selling an asset.

Again, we distinguish between buy and sell side in order to determine events that are unfavorable. For a *Buy Passive* strategy which aims at buying a stock by posting bid limit orders an increase in the volume of the bid side during the time of order submission and reception by the exchange would be disadvantageous as the order is further behind others according to price/time priority in open order books. Figure 17 depicts such a situation. Order volumes are written in the circles. Thus the next incoming market order of 31 shares would execute against the fist two orders of 8 and 23 respectively leaving the last order untouched.

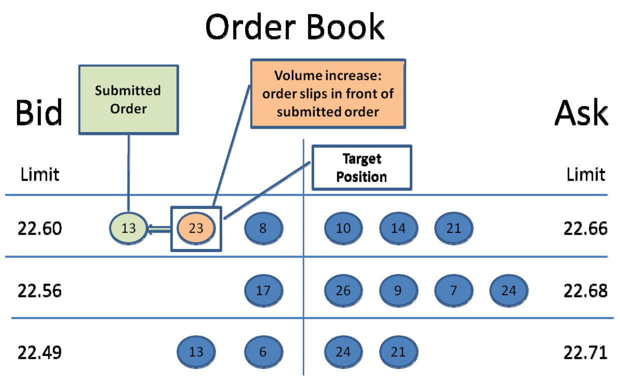

Figure 17: Effects of Latency on a Trader's Order Submission

Also any bid limit change can be regarded as a negative event. This is because the order has either been overtaken by another limit order with a higher bid or orders have been taken away leaving the order with a possibly to high limit in the order book and what is more with a high execution probability.

Accordingly, for the *Sell Passive* strategy increases in volume at the top of the ask side and any limit change in the ask limit are regarded negative.

A summary of changes which are considered negative for the four basic strategies is given in table 18.

Property / Side	Buy	Sell
Active	Ask Limit ↑ Ask Volume ↓	Bid Limit ↓ Bid Volume ↓
Passive	Bid Limit ↕ Bid Volume ↑	Ask Limit ↕ Ask Volume ↑

Table 18: Unfavorable Top of the Book Changes

3.3 Estimation

Due to the model's simple structure finding estimators for $p_{fluc}(x)$ is straightforward. We take the relative frequency in which order book changes occurred in the past. As reasonable time spans we will take latency in the range of those reported by Schweickert and Budimir (2009).

Estimators for limit and volume changes can be derived by taking the mean of the quoted volume and limit changes in the time span for which $p_{fluc}(x)$ is estimated.

4 Dataset

The impact of latencies in magnitudes of milliseconds is of particular interest for algorithmic traders as even such little speed advantages can provide them a competitive edge. Algorithms require fully-electronic open central limit order books and a remote access via technologies like direct market access to be applicable. Thus we choose the XETRA trading system of Deutsche Börse for our analysis. Typically algorithms are employed for instruments with high trade volumes (high liquidity). A proxy therefore is capitalization, which is also utilized for index weights. Thus capitalization expresses the particular interest of investors for each instrument. The 30 most capitalized instruments in Germany are represented in the DAX. As expected this index exhibits on XETRA most algorithmic activity (Schweickert and Budimir 2009).

To allow a cross-sectional overview we choose 6 DAX constituents based on their free float market capitalization. That way a pair of two instruments is employed for three different capitalization classes: Siemens and E.ON as high; Deutsche Börse and Deutsche Post as medium and Salzgitter and Hannover Rück as low capitalized constituents (cf. table 19).

The employed capitalization data (cf. table 19) belongs to our last observation day. Nevertheless, it is checked to remain stable during the whole sample period. It is made of 10 trading days starting from August 31st, 2009 and ending at September 11th. Results remain stable for the first and second week of our sample implying that the 10 selected trading days are sufficient. To obtain unbiased results we avoided periods of extreme market activity by expiry dates like so called Triple Witching Days or high market volatility. In contrast the VDAX-New, which can be interpreted as a trend indicator for the volatility of the DAX, exhibits a stable and rather low value compared to the US sub-prime crisis already since August 2009.

Our data set originates from the archives of Thomson Reuters Data Scope Tick History. For the selected instruments all order book updates are retrieved. These updates consist of the first ten quoted limits and volumes on both sides of the book, i.e. the ten highest bid and ten lowest ask limits. Each change within these limits results in an update record. For multiple changes, occurring within one millisecond, we account only for the last one, as investors with the investigated latencies of above 1ms are not able to react pointedly to such instant changes. Finally, we restrict our analysis to the limit and volume changes of the best bid/ask as algorithmic activity can be predominately found at the top of the book (Gsell and Gomber 2009).

The focus of our investigation is set on continuous trading where order book changes as well as trades can occur at any times. For DAX instruments continuous trading takes place from 9:00 till 13:00 o'clock in the morning and 13:02 till 17:30 in the afternoon. Accordingly, order book updates for auctions are removed and validity times of the last limit updates before auctions adjusted appropriately. Unfortunately, our data lacks secured information on volatility interruptions. But as this mechanism

Capitalization Class	Instrument	Free Float Market Capitalization [m€]	Order Book Top					
			Lifetime [ms]		Fraction of Changes [%]		Mean Quoted Volume [€]	
			Mean	Std. Dev.	Limits	Volumes	Best Bid	Best Ask
High	E.ON	57,829	1,129	2,758	19.91	80.09	94,911	96,184
	Siemens	52,070	860	2,342	30.55	69.45	60,205	60,263
Medium	Deutsche Börse	10,902	925	3,216	35.30	64.70	30,645	28,381
	Deutsche Post	10,673	1,507	4,168	21.45	78.55	51,268	45,798
Low	Salzgitter	2,673	1,255	4,189	34.42	65.58	22,849	22,975
	Hannover Rück	1,785	4,020	10,085	33.25	66.75	23,914	25,052

Table 19: DAX Order Book Data Sample Characteristics

to switch from continuous trading to an auction results in one limit change per interruption and occurs seldom, its effects are expected to be smoothed out by the multitude of order book updates observed.

Table 19 depicts the basic characteristics of the data set described above: Besides, the free float market capitalizations for our three classes, mean lifetimes of top of the book situations, fractions of limit and volume changes as well as the mean quoted volume for the best bid/ask are depicted. No general conclusion can be drawn that lower capitalized instruments' best bid/ask limits and volumes exhibit lower lifetimes. Nevertheless, standard deviations of lifetimes are generally high and increase for lower capitalizations. Further, there are about twice to four times more volume than limit changes. Basically the fraction of limit changes increases with lower capitalizations. This is obvious as lower capitalizations come along with lower quoted volumes and thus induce more trades to completely remove the volume of the targeted limit level. As limit price changes come generally along with different volumes the depicted numbers reflect only such volume changes without simultaneous limit alterations.

5 Measurement and Results

5.1 Measurement

For our goal to find a universal and neutral measure for impact of latency we try to assume as few as possible restrictions by a specific trading strategy. Consequently, our measurement procedures are not based on strategy specific information such as: when an individual trader submits orders, receives executions, which kind of orders are used or how harmful unexecuted orders for her strategy might be. Instead we take a general perspective and aim at investigating the expected probability of relevant order book alterations as well as the expected magnitude of such alterations.

Further, as we expect day patterns within our data, trading days are divided into investigation intervals: The shorter these intervals the more flicker arises whereas longer interval potentially might smooth out patterns. Therefore, we checked different interval lengths. Overall the found patterns remain stable. For the illustration below an exemplary interval length of 15 minutes is chosen.

For each interval of a trading day (34 for a length of 15 minutes) we calculated the probability of being hit by an order book change within a given latency delay. This is carried out for any change for the strategy independent measure and for relevant changes for the four simple strategies as described in sections 3.2.2 and 3.2.3. Besides, the magnitude in volume and limit price changes at the top of the book (i.e. for the best-bid/ask limits) are calculated.

For all calculations we applied a sliding window. It compares the order book situation at a time m_i with that after an assumed latency delay x milliseconds later, i.e. at $m_i + x$. This window slides through every millisecond of an interval. In every millisecond, where we can find a relevant change after x milliseconds, we increase our number of relevant observations by one. At the end of each interval we divide the number of observations by the amount of milliseconds in that interval, i.e. 900,000ms in case of 15min interval. As an estimator for the probability of a (relevant) order book change we take the average of the ten trading days for each interval of those ratios.

Because an order could be submitted in any millisecond this ratio estimates the probability of being hit by an order book change when submitting an order at any time in the interval. Variations of the window size, which simulates our latency delay, are set from 5 to 100ms in 5ms steps to assess latency impacts over typical traders' latency experiences (Schweickert and Budimir 2009). Additionally, latencies of 1 and 2ms are included to focus border cases. To assess the impact of those changes we also measured the average limit and volume changes within those time spans.

Limit price changes typically come along with volume changes. Thus, we only account for such volume alterations where the limit price remains unchanged to avoid overestimations of the alteration probability.

5.2 Day Pattern in Order Book Fluctuations

As expected the probability of alterations clearly shows a significant day pattern. The trend of the average probability for our four basic strategies and the overall measure of limit and volume changes for a latency of 10ms is depicted in figure 18. Basically one can see that all 5 lines exhibit the same form that is only shifted upwards or downwards. As the top line in the graph accounts for all kind of changes it takes the highest probabilities. The two next lines represent the passive (buy/sell) strategies and the two last with the lowest probabilities correspond to the active (buy/sell) strategies. Obviously there are no striking differences among the buy/sell pairs of active or passive strategies as the corresponding best-bid/ask limits are symmetric around the instruments midpoint. Further, the fact that passive strategies exhibit higher probabilities to be effected by order book alterations is due to the fact that they account for three kinds of changes whereas active strategies do only for two.

Concerning the overall trend all five lines share a modified U-shape which can be also observed for trading volumes (Abhyankar et al. 1997; Stephan and Whaley 1990). Thus, in the morning the probability of order book alteration is high and decreases continuously. It reaches its minimum just after the midday-auction. Then it increases again. Different to typical volume U-shapes it falls sharply again at ∼14:30. Then a striking large increase occurs at approx. 15:30. This is congruent with the opening time of the US markets.

The line with the highest probabilities represents the case, where any change in the order book is viewed as disadvantageous. As stated before this is an entirely strategy independent measure, which could be useful for an infrastructure provider, who does not have access to any information about the algorithms that use the infrastructure.

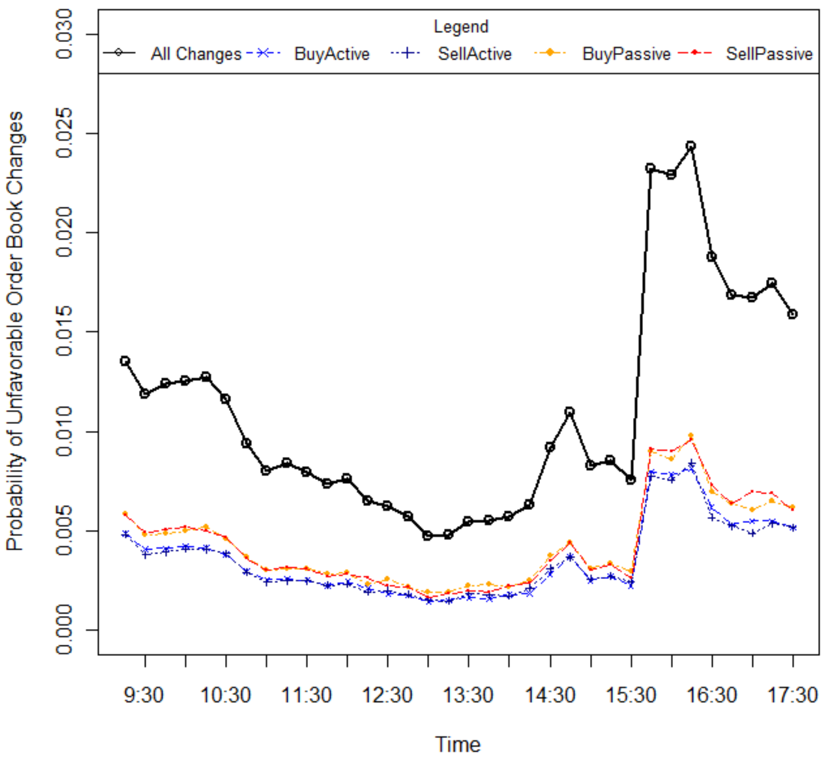

Figure 18: Order Book Alteration in the Course of the Trading Day for Siemens and 10ms Latency

5.3 Latency Impact

The length of the latency delay has of course an impact on the probability that the order book situation changes in a way that seems unfavorable for a submitted order. A first hint as to how much this influences the pattern can be seen in figure 19.

The graph shows the day patterns for 10 to 100ms for a Buy Active strategy in E.ON. The lowest line represents the probabilities for a 10ms delay, the next higher line 20ms etc. We omit the 5ms step here for demonstration purpose. It can already be seen at this point that the day pattern is not only preserved but even amplified by the latency effect.

In consideration of this fact latency impact is examined for every 15min interval separately. In every interval the effect of latency on the probability of unfavorable order book changes shows a typical slightly concave relation. This concave effect on the probability can be found in any interval across all stocks and for all strategies in our sample. The graph in figure 20 depicts the average increase of probabilities for a Buy Active strategy in E.ON. The empiric values can be fitted with a log-linear regression.

From the slope of this regression we can deduce the following simple rule of thumb. A 1% increase in latency leads to a 0.9% increase in the probability of unfavorable order book changes.

Thus, reducing latency about 1ms has a greater effect on the probability the lower the latency already is. Due to data restrictions our study only covers latencies from 1ms

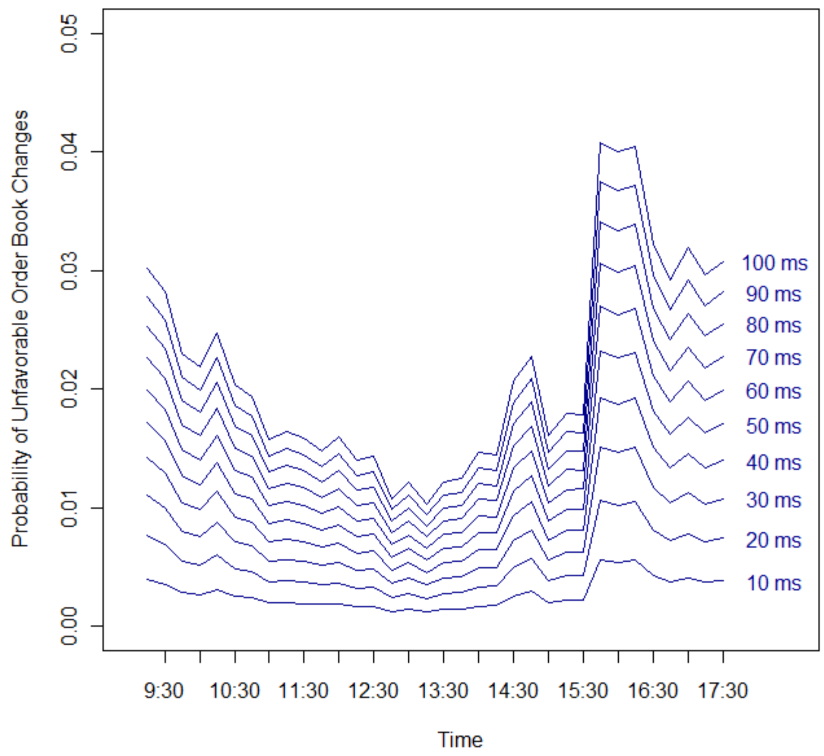

Figure 19: Day Pattern for E.ON and Latencies of 10 – 100ms

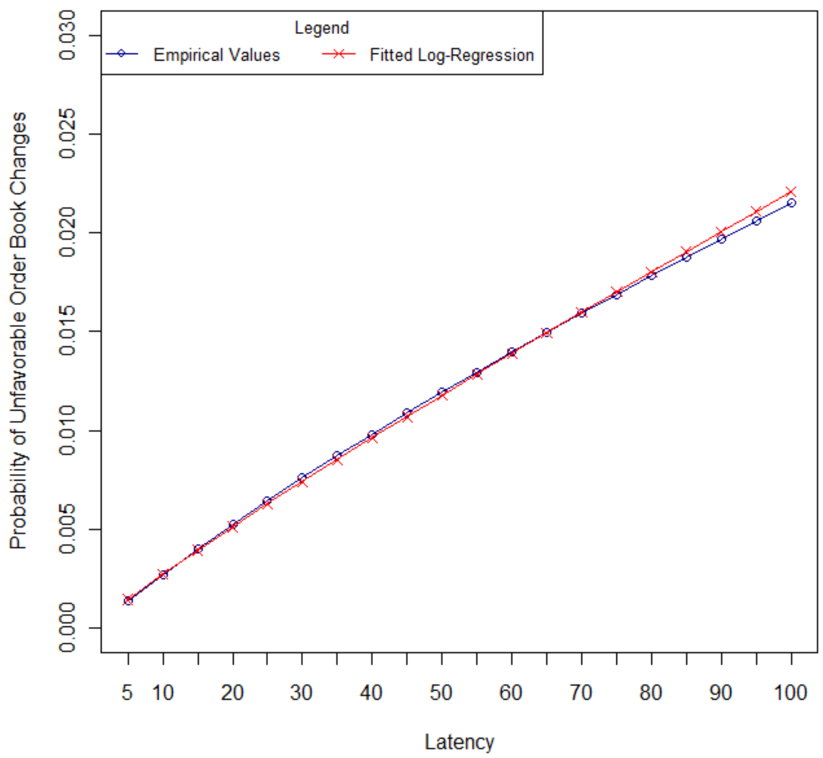

Figure 20: Scaling of Hit Probability Due to Latency

upwards. However, with more accurate data and an extension in the submillisecond area this might provide an additional explanation why high investments in relatively small improvements in latency can be found in the market.

5.4 The Influence of Market Capitalization

As depicted in the introduction heavily traded stocks will be more prone to latency risk. Since market capitalization is a fairly good proxy for the interest of traders in the stock (cf. section 4) we expect highly capitalized stocks to exhibit a higher probability and a higher latency impact than lower capitalized ones.

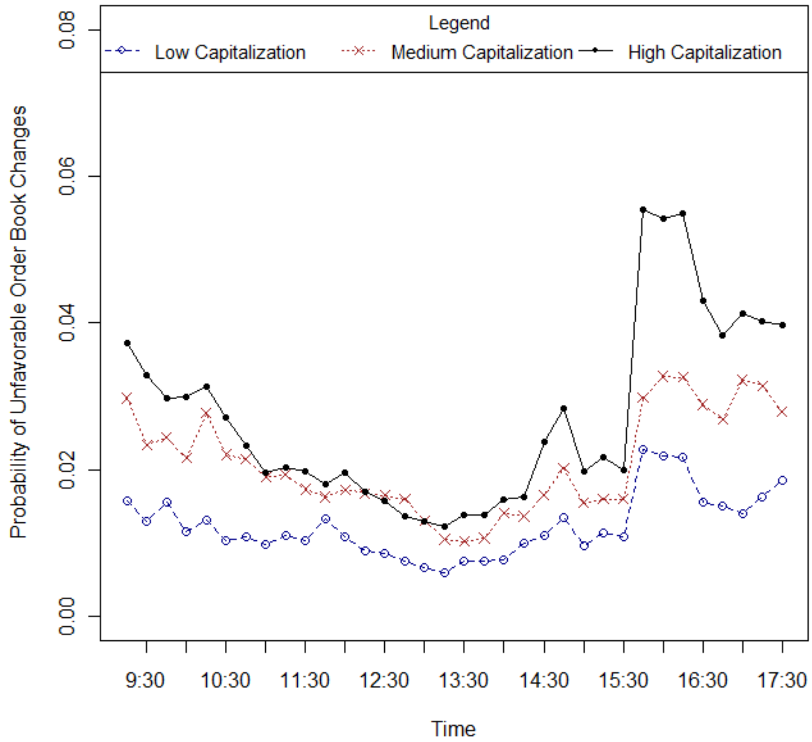

Figure 21: Hit Rate for our Three Capitalization Classes

Figure 21 clearly confirms this assumption. Highly capitalized stock's probability of unfavorable order book changes is on average twice as high than those of low capitalized stocks. The figure shows the day patterns of probabilities for a Buy Active strategy and a latency of 50ms for the three classes *low*, *medium* and *high* capitalization.

5.5 Average Limit and Volume Changes

Though day patterns are common for limits, prices, spreads and volumes in stock trading, it remains unclear how changes of limits and volumes within latency delay evolve over time. Among others e.g. (Abhyankar et al. 1997; Stephan and Whaley 1990) find typical U-shape of trading volumes. This is congruent with our results. However, the risk that one faces due to latency rather depends on the amount of changes in volumes within the order book than on the overall trading volume.

To our best knowledge we do not know any study that examined the average amount by which limit and volume change. In order to combine information of those changes with the probabilities from the previous paragraphs, we use the same sliding window measurement method as before. That is, we compare the limits and volumes after an assumed latency delay and take the average after every 15min. Limit decreases are measured relatively in basis points (1bps = 0.01%) to allow for comparisons among different stocks.

In case of volume changes we could not find any significant trend, which is stable over all stocks and trading days, whereas limit changes show a significant decrease in a trading day. Therefore, for a typical volume change one should take the average for the whole trading day as an approximation. Changes in limits tend to be higher in the morning than in the evening. As described before limit changes are higher in the morning. A typical example is shown in figure 22.

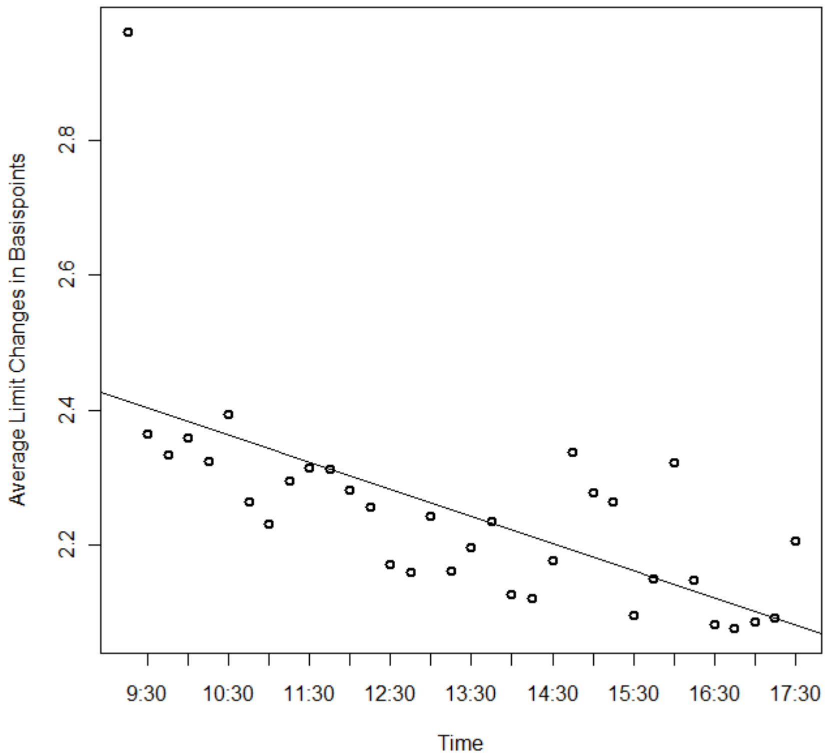

Figure 22: Evolution of Limit Changes in E.ON

The graph shows the sum of absolute values of changes in bid limits in basis points, averaged over ten trading days in E.ON. The line is that of the linear regression that exhibit a highly significant p-value (at the 1% level or more) for all cases, except for Hannover Rück, where significance can only be found at the 10% level.[3]

Interestingly this does not reflect a typical U-shaped volatility pattern. But since limit changes do not necessarily reflect price changes this does not contradict results concerning price volatility.

[3]Changes in ask limits reveal the same tendency. Significant decreases can be found for all stocks except for Salzgitter.

6 Discussion

6.1 Impact on Active Strategies

For market or marketable limit orders, i.e. the means to implement an active strategy, two unfavorable situations can be encountered (cf. table 18): an unfavorable movement of the limit price or a decrease of its volume. To assess their impact we make use of probabilities discussed in the last section. For actual executions the assessment of limit price changes is straight forward as they can be directly converted into costs. Therefore, we take the probability of such changes times the expected limit change:

$$\begin{aligned} E(LimitChangeCosts) &= p_{LimitChange} \cdot E(LimitChange) \\ &= p_{fluc} \cdot P(LimitChange|fluc) \cdot E(LimitChange) \end{aligned} \tag{1}$$

As we have encountered significant trends within the limit changes (cf. section 5.5) and day patterns for the probability to be hit by them (cf. section 5.2) we calculate these figures for each interval. Again, we encountered a U-shape for the expected limit change costs. An overview of their magnitudes is provided in table 20 for an active buy strategy and an assumed latency of 50ms. The latency cost impact ranges between 0.01 and 0.06bps. Basically differences among instruments highly depend on the proportion of unfavorable limit price to volume changes. This is also the rationale behind the low figures for the highly capitalized instruments E.ON and Siemens.

Instrument	Limit Change Costs [bps]			
	Min	Max	Mean Std.	Dev.
E.ON	0.0133	0.0509	0.0275	0.0114
Siemens	0.0140	0.0617	0.0310	0.0140
Deutsche Börse	0.0188	0.0625	0.0382	0.0113
Deutsche Post	0.0124	0.0522	0.0280	0.0109
Salzgitter	0.0150	0.0453	0.0263	0.0084
Hannover Rück	0.0093	0.0363	0.0186	0.0077
Overall (Average)	0.0093	0.0625	0.0282	0.0126

Table 20: Buy Executions Limit Change Costs – 50ms Latency

Overall this part of the latency impact costs is low compared to typical implicit trading costs (i.e. market impact, timing or opportunity costs). Nevertheless, for strategies yielding only low profits per trade, like those of HFTs, these figures become relevant: For example the US HFT Tradeworx (Narang 2010) reports average net earnings of 0.1cent per traded share. With an average share price of 41.84$ within the S&P 500 this corresponds to net earnings of 0.24bps. Hence, the sole limit change impact for an active strategy with latencies of 50ms might diminish their profits by as much as 26%.

While market and marketable orders face the costs described above in case of executions, it can also happen that due to latency marketable orders cannot be executed. For this situation no direct costs can be associated but a loss of immediacy. Depending on the underlying strategy cost of immediacy need to be assigned if one wants to model the limit change costs completely.

For the second component of the latency impact, i.e. decreasing volume, exact cost figures cannot be calculated without knowledge of the underlying strategy either. Nevertheless, our figures show that e.g. in E.ON an average volume decrease of 29% occurs with a probability of 1.7 – 6.7% depending on the order submission day time. This is particularly harmful for algorithms, which aim at taking advantage of promising trade opportunities as much as possible. For XETRA we know that 76.7% of all orders that exactly match the best bid/asks and volume are submitted by algorithms (Gsell and Gomber 2009). Further, 17.7% of such orders submitted by algorithms succeed in match the best bid/ask and volume.

6.2 Impact on Passive Strategies

Limit and volume changes result in wrong positioning of the submitted limit order in the order book. For an exemplary buy order a best ask limit increase the order is placed too far up the book, whereas decreases lead to a position below the top. At last the volume effect is opposite to that of the active strategies. An increase in the volume of the top of the order book puts the limit order at a more distant position regarding the price/time priority thus diminishing the execution probability. This effect has already been illustrated in figure 17. The targeted position is taken by another order that entered the book within the latency delay. The submitted order is now behind this order. The next incoming order that triggers a trade will be matched against this order before the submitted order. It may well happen that this effect hinders submitted orders to be executed at all when marketable sell order volumes are small.

Passive strategies aim at saving or earning the spread, i.e. they seek price improvement at the cost of execution probability. The latency effect decreases the execution probability. Therefore the low latency trader can seek more price improvements than a trader who has to bear high latency. Our figures show that volume changes occur far more often than limit changes (cf. table 19), in our sample up to four times more often. This is not captured in volatility or other standard parameters usually reported for stocks.

In this study we calculated the probabilities of the occurrence of relevant volume and limit changes. The impact of latency can in this respect be regarded as an impact on the error rate of order submission.

Mean volume increases are about 147.7% with a standard deviation of 73.5%. But the maximum of 15min average volume changes we found was (at 9:15–9:30 for Hannover Rück) 583.5%. E.g. a trader with a latency of 50ms has to expect for E.ON that there is a 2.9% chance that her order will be *overtaken* by another incoming limit orders increasing the existing volume by 147.7%.

Since it would be desirable to assign costs to these numbers, strategy independent models need to be applied to assess the impact of those effects on execution probabilities and then to convert these into trading costs. This extension is not in the scope of this study but builds an interesting field of future work.

7 Conclusion

This paper examines the effects of latency in securities trading. Based on data for DAX instruments traded at XETRA fluctuations at the top of the order book are analyzed. These fluctuations encompass limit and volume changes. To assess their impact on securities trading four fundamental strategies are dealt with.

Concerning our first research question on the effects of latency we show that latency impact differs significantly among instruments: In general highly capitalized stocks exhibit higher probabilities to encounter unfavorable order book changes during the latency delay than lower capitalized ones. Among fluctuations volume changes occur twice to four times more often than limit alterations. Further, for all strategies a significant day pattern for the probability of unfavorable changes is found. Thereby, passive strategies based on non marketable limit orders are more often affected by order book changes than active ones. For commonly observed latencies at XETRA (1 to 100ms) the dependence of probabilities for unfavorable events turns out to be non-linearly increasing with latency. Nevertheless, they can be fairly well approximated by a log-linear regression.

Regarding the scale of relative changes, limit alterations significantly decrease over the trading day whereas for volumes no common day trend can be found. Limit increases and decreases are symmetric. Further, volume increases are typically higher than decreases, which is obvious as decreases cannot exceed 100%.

To answer our second research questions, whether these latency effects require market participants to employ low latency technology, we investigated four fundamental trading strategies. For these the calculation of directly associated cost is only applicable for active ones. Passive strategies cannot be associated with direct costs without further assumptions regarding the true underlying trading strategy. In this case we present average latency effects regarding the limit and volume effect market participants face. That way buy and sell strategies do not exhibit significant deviations.

From an exchange's customer perspective the following conclusions can be drawn: For each individual retail investor, who cannot make use of low latency technologies, price effects are neglectable. Also volume effects seem irrelevant as retail trade sizes are typically low compared to quoted best bid/ask volumes. For institutional investors the answer depends on their business model: Basically for algorithmic traders latency effects yield low increases of error rates. For investors whose business follows long term profits this latency effects seem bearable. In contrast the lower the profits associated to each trade are the more fatal these effects become.

Future research steps should include an extension of the cost analysis to passive strategies and the volume effect of active strategies. Therefore, it should aim at incorporating estimations for execution probabilities and models for the cost of immediacy.

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Paper 5

Assessing IT-Supported Securities Trading: A Benchmarking Model and Empirical Analysis

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Americas Conference on Information Systems Proceedings (AMCIS 2010), Paper 476, BEST PAPER AWARD NOMINEE, Lima, Peru, 2010

Abstract

Information technology plays a major role to support the process of securities trading. Tactical trading decisions can be implemented more efficiently by gaining access to alternative trading systems, which provide access to additional liquidity and potentially better execution prices. This paper explores the business value provided by to so-called dark pools of liquidity, which can be accessed by adjusting the trading process and adopting new IT. With limited access to large investors, dark pools represent alternative trading systems with a focus on very large volumes between selected institutions. We aim at exploring the potential business value provided to investors deciding to implement the necessary requirements. Therefore, a benchmarking approach is presented to compare dark pool executions with prices, which were available at traditional stock exchanges. The empirical results provide evidence for significant price improvements, which can be realized when gaining access to darks pools, especially when trading very large orders.

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1 Introduction

The process of securities trading, which aims at turning an investment decision into a portfolio position, has faced a significant change and gained much complexity in recent years. While access to more stock exchanges and to an increasing amount of alternative trading systems (ATS) provides new opportunities, this complexity demands for more IT to support the trading process. Adopting IT in this field for example means gaining access to additional markets and to new liquidity, which was not available before.

Measuring the business value provided by IT is an important research subjects in IS research since many years (Brynjolfsson 1993; Chan 2000). One major research stream in this field has a focus on how IT improves business profitability and how this improvement can be measured, for example on the basis of performance metrics (Hitt and Brynjolfsson 1996). The concept of business profitability is derived from theory of competitive strategy, which states that companies are not able to capture the value of specific investments over time since all competitors will adopt or invest in new beneficial approaches or infrastructure, such as technology (Porter 1980). However, if there exists entry barriers (e.g. patents or capital intensive IT systems), which prevent other market players from adopting the same technology, this can lead to increased profitability (Philip et al. 1995).

In this paper, we will explore such an example, which prevents some market players from adopting a certain technology, which competitors are able to use. However, such a barrier does not automatically lead to increasing success. In securities trading, it might be the case that adopting a technology (providing access to a new market) does not lead to any benefits, because comparable prices and liquidity might be available at other markets, which can be accessed easily. In securities trading, so-called dark pools represent such alternative markets, which demand for changes in the traditional trading process and the underlying IT. Having a focus on very large trades (so-called block trades) these markets restrict access to large investors with a high value of assets under management (AuM), representing a significant barrier to entry.

Against this background, we aim at exploring whether investors who adopt the technology to access such dark pools can realize significant benefits. Our analysis is based on a benchmarking approach. Since benchmarking has the objective to measure and compare organizational performance (e.g. of the trading process) against competitors, we collected a dataset of trades, which were reported by one exemplary large dark pool called Liquidnet. A conceptual model is presented for comparing the trading outcomes with prices, which would have been available at traditional stock exchanges. Our research will provide insights on how competing investors are implementing IT-enabled changes of the tactical investment management processes and whether – and, if so, under which conditions – they can realize substantial benefits.

The paper is organized as follows: In the next section, we will present an introduction to IT-supported securities trading and the success story of darks pools. Then, we will present a benchmarking model which provides means to compare and benchmark trades which have been executed via an alternative trading system. The case of Liquidnet, which we have chosen as a representative dark pool, is then presented including its characteristics, market model and the IT-based change of the securities trading process. After that we will provide insights into the analyzed datasets. The empirical results show the potential benefits and provide further evidence in which scenarios these benefits can be achieved. We conclude with a summary and an outlook on further research.

2 The Success Story of Dark Pools in Securities Trading

Within the last decades traditional floor-based exchanges have undergone an IT-driven transformation towards fully automated electronic trading systems (Schwartz and Francioni 2004). No matter whether a quote-driven dealer market or an order-driven electronic order book is employed, there is no need to be present at an exchange's trading floor anymore. Nowadays, exchanges offer remote access and thus enable fast dissemination of price changes to its participants. Although this electronification of securities trading leads to increasing trade volumes, which are supposed to improve price discovery, (i.e. the determination of an instruments fair equilibrium value) one can observe a trend towards decreasing average transaction sizes among major exchanges (Grant 2010). For institutional investors, who predominately trigger trading activity on nowadays security markets (Schwartz and Francioni 2004), this trend aggravates the *order exposure problem* (Harris 2003). Although their large trade intentions are instrumental for the determination of a consensus value, institutional investors are reluctant to expose their large orders (block orders) for price discovery. In transparent markets, this immediately will result in negative price movements (market impact). This phenomenon is caused by the information large trade intentions signal to security markets: Firstly, they exert buy or sell pressure on the market during their execution. Secondly, the pure existence of large unfilled orders is interpreted as an imbalance of supply and demand by other market participants. This issue let block orders become vulnerable to front running. Here, other market participants, who become aware of a large trade intention, try to trade ahead of it. In doing so, they aim at taking advantage of the market impact induced by the original large volume. Simultaneously, this practice further influences prices negatively (Harris 2003). Thus, anonymity is of major importance for institutional investors. As volume discovery, i.e. finding of adequate counterparties, for large trade intentions is complex at nowadays transparent exchanges, specialized market models have evolved. One kind of these alternative trading facilities are dark pools of liquidity.

In general, dark pools represent IT-based extensions of traditional upstairs markets, which are anonymous and fully confidential (Gresse 2006). Their objective is to allow institutional investors trading large order volumes without market impact. Therefore, these systems aim at minimizing information leakage concerning their members' trade intentions, i.e. they do not display quotations to the open market (Skinner 2007). Accordingly, dark pools do not participate in price discovery. Instead they often use derivative pricing rules.

The main distinctive feature among dark pools is their *market model*, i.e. the rules how information on trade intentions are matched to actual trades. The most traditional dark pool type are crossing networks like ITG's POSIT (Harris 2003): These systems are based on a closed order book. The actual trade prices are independent of the trade interests, which are sent to the crossing network. Instead, actual trade prices are derived from another reference market. Thus, their price quality depends on the selected market's price discovery mechanism (Conrad et al. 2003). Typically, crossing networks choose the midpoint, the day's closing price or the volume weighted average price of a predefined period. Further, fill rates are of particular importance as trading is characterized by strong network effects (Schwartz and Francioni 2004). Therefore, a successful dark pool requires exceeding a minimum trading volume (liquidity) to become attractive to its members (Conrad et al. 2003). Typically, crossing networks exhibit low fill rates below 10% of the submitted volume (Harris 2003; Næs and Ødegaard 2006).

To overcome this issue, multiple dark pool approaches have originated in the USA. Mittal (2008) provides a taxonomy and detailed description of their differences. Altogether, already more than 40 different dark pools operate in the US and cover approximately 9% of the overall trading volume (Spicer 2009; The Economist 2009). One type, which has attracted particular attention, are so called full service broker dark pools. They obtain the required minimum liquidity by executing client orders against the broker's own order flow (proprietary trading). Further, their executions are only reported as over-the-counter trades without indicating the actual trade venue. Because of this missing post-trade transparency and their ongoing market share growth, the US Securities and Exchange Commission investigates whether the segmentation of order flow caused by this kind of dark pools in combination with their low transparency negatively affects price discovery (Spicer 2009). In contrast, traditional agency broker dark pools such as POSIT or Liquidnet allow only executions among client orders. Further, their trade reports allow identifying them as the trade venue employed, which is the basis for this research. To attract enough liquidity, agency broker dark pools require sophisticated market models, which provide value to their customers' trading.

Different to the US, dark pools are still establishing themselves in Europe. One important facilitator for their growth is the introduction of the Market in Financial Directive (MiFID) in November 2007. MiFID has ended the concentration of stock trading at national stock exchanges in various European member states. Thereby it fosters competition among trading venues as it allows off-exchange trading at so-called multilateral trading facilities. Accordingly, the number and trade volumes of dark pools are steadily increasing in Europe (The Economist 2009). Thomson Reuters (2012) reports trading volumes among European non-displayed order books to have risen from 2.2bn€ in January to 8.6bn€ in December 2009, which is illustrated in figure 23.

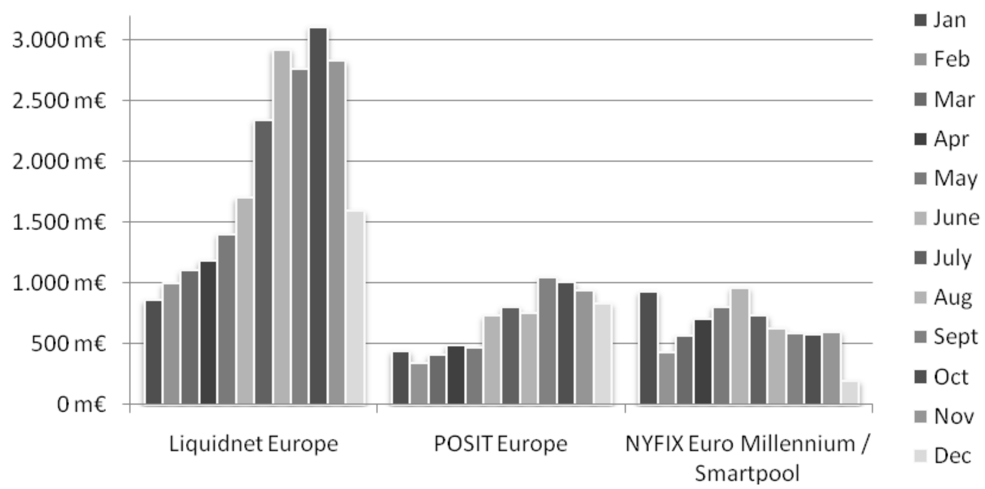

Figure 23: Execution Volumes among Selected European Dark Pools in 2009

3 A Conceptual Model on Securities Trading Benchmarking

To benchmark trade executions which have been observed for a given dark pool, we have developed a conceptual model, which compares and benchmarks prices with those being available at the home market of the corresponding security. In contrast to most benchmarking concepts, which have a focus on competitors in order to benchmark organizational performance compared to a peer group (Drew 1997), our conceptual model uses market data from a securities home market. This, for example, would be for US company shares quotes from NYSE or NASDAQ or for European company shares the corresponding limit prices and volumes from the national stock exchange.

The model is based on an assumption regarding the initiator-side of a trade and determines whether a trade is sell- or buy-initiated. If the price observed is lower (higher) than the midpoint price of the home market (which is the midpoint between the best bid and the best ask), a trade is defined as *sell-initiated* (*buy-initiated*). This assumption is based on two arguments: First, an initiator of a block trade will give price concession to attract liquidity (Harris 2003). Second, our benchmark should be a conservative measure and therefore has a focus on the side for which the negotiated price is less attractive (Sarkar and Schwartz 2009). Based on this assumption, we define a price improvement PI as follows:

$$PI_i = halfspread_i - \left|p_{Venue,i} - p_{home\ market,\ Midpoint,\ i}\right|$$

with:

$$
\begin{aligned}
\textit{half spread} &= \frac{\textit{best ask} - \textit{best bid}}{2} \\
PI_i &= \textit{price improvement} \\
p_{Venue,i} &= \textit{price observed at the ATS} \\
p_{\textit{home market, Midpoint, i}} &= \textit{midpoint observed at the home} \\
&\quad \textit{market of the security} \\
i &= \textit{index of trade observed}
\end{aligned}
$$

Figure 24 illustrates our model indicating two hypothetical executions. Trade i, which has been observed at $p_{Venue,i}$, is assumed to be sell-initiated because it is lower than the midpoint. Since $p_{Venue,i}$ is outside the bid-ask spread, it shows a negative price improvement. In contrast, $p_{Venue,i+1}$ is higher than the midpoint, i.e. a buy-initiated trade, which has been observed within the bid-ask spread. It consequently features a positive price improvement.

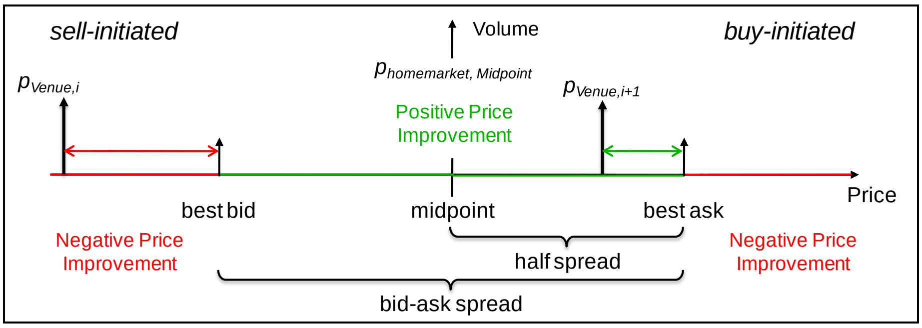

Figure 24: Securities Trading Benchmarking Model

To allow comparison among instruments with different values, we analyze this *price improvement PI* relative to the instrument's midpoint price measured in basis points (0.01%). Therefore we define a *relative PI* as:

$$\textit{relative PI} = \frac{PI_i}{p_{midpoint}} \cdot 10.000$$

The *relative PI* is used in order to benchmark executions, which have been observed on an alternative trading system, with one of them presented more detailed in the following.

4 The Case of Liquidnet

Liquidnet belongs to the largest agency broker dark pools (Harris 2003). As depicted in figure 23 its trading volume is still increasing. One reason for its acceptance is the unique market model Liquidnet employs (Harris 2003): Basically this model attempts to add more flexibility to traditional crossing networks. Therefore, traders do not need to submit orders to Liquidnet. Instead, the system searches for matching trade intentions from the investors order management systems (OMS). Further, potential matches are signaled to the respective traders, which can enter anonymous negotiations. This advertisement-based approach risks disclosing information about trade intentions. Thus, several mechanisms like a closed user group are incorporated to minimize information leakage.

Figure 25 highlights the information flow within Liquidnet's (2001) three-step market model: First, Liquidnet retrieves trade intentions from its clients' OMSs on a continuous basis. Besides the instrument and the buying or selling intention investors at a connected trading desk can specify their desired order size as well as a minimum tolerance level for potential counterparties. Based on the collected information, a decentralized search within Liquidnet's peer-to-peer network is performed. Up to that point, information concerning the trade intentions and involved investors are kept completely confidential. After suitable counterparties are identified, the system remains passive, i.e. no executions are triggered. The second step of indicating existing counterparties is triggered only when the trade volumes of both investors exceed the other's tolerance level. In doing so the involved institutions' identities are kept private. Further, the original trade volumes remain undisclosed, too (Mittal 2008). At this point the involved investors can decide to enter anonymous bilateral negotiations, which are the third and final step. During these negotiations the actual trade volume as well as the price can be determined.

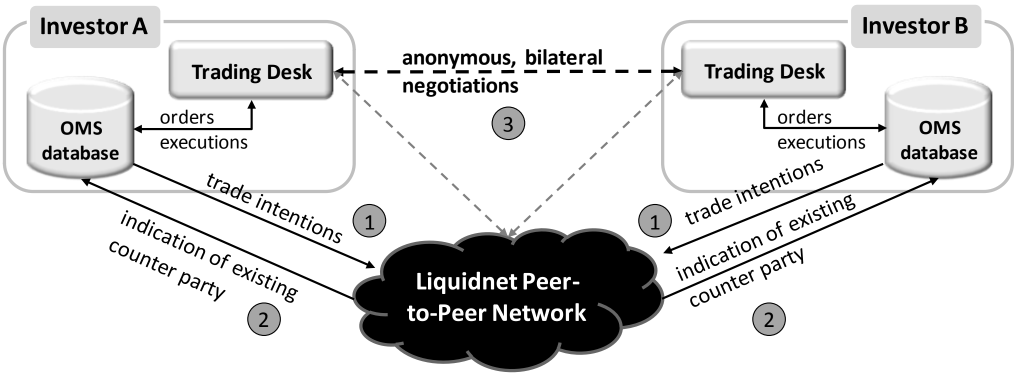

Figure 25: Market Model of Liquidnet

As mentioned above Liquidnet pursues multiple strategies to restrict the group of investors, who are informed about its clients' trade intentions to minimize information leakage: First, Liquidnet employs barriers to entry to form a closed and homogenous user group of buy-side[1] only users. Further, customers are restricted to posses more than 500m$ AuM (Schwartz 2009). As of end 2009, these were 592 member firms worldwide with above 27bn€ AuM on average (Liquidnet 2009). The closed user group approach aims at avoiding trade intentions to be disseminated to market participants, whose business is to take advantage of their existence. In addition,

[1]Buy-side refers to investment companies that are buying trading services from the sell-side, i.e. investment banks and brokers (Harris 2003).

members are supposed to utilize OMSs. This restriction is a further safeguard against clients gaming the network as OMSs are said to exhibit only true trade intentions. On top, Liquidnet also monitors its members' trading activity. This is important as the indications of counterparties can be used to infer at least a lower boundary for existing trade intentions, namely one's own lower volume threshold. Thus members, who are not interested in completing trades, might take advantage of this information. To impede this practice known as fading, clients might be excluded from the network.

Another important aspect of Liquidnet's decentralized negotiation mechanism is that investors retain the control of their orders, i.e. no committed orders are used. In contrast, most dark pools are designed as centralized systems. Thus, trade intensions which are brought to these systems are always committed. Although unexecuted orders can be canceled, traders have no control until they receive a final acknowledgement of their cancelation. Consequently, if they send their orders to multiple of these systems, they risk their volume to be executed many times. Thus, an investor can interpret Liquidnet as a further option to trade. This nature is also incentivized by Liquidnet's pricing scheme: No installation or minimum fees are charged before actual executions take place (Liquidnet 2001). However, an adjustment of the IT, which supports the trading process, is required and traders have to be trained extensively to use the new venue appropriately. The commissions to be paid for negotiated trades are said to be 7bps (Mehta 2007). Compared to traditional exchanges or multilateral trading facilities in Europe like Chi-X (who charge below 0.5bps) these explicit costs appear quite high. But as conservative estimates by Bikker et al. (2007) suppose average market impact costs to be 20bps for buy and even 30bps for large sell orders, the value of Liquidnet depends on its negotiated execution prices.

Finally, as the likelihood to fill an order is an important factor for a dark pool's quality, Liquidnet has recently been employing secondary strategies, which aim at integrating sell-side liquidity. This increased the filled latent liquidity provided by its members – the following numbers are based on US equities only – from approximately 14% to 21.5% (SEC 2008). Nevertheless, as an optional offer to its members, this does not violate its general strategy of a closed buy-side user group.

5 Dataset Description

The employed dataset originates from the archives of Thomson Reuters Data Scope Tick History. It includes two types of information, whose time stamps are based on milliseconds: First, from the Markit BOAT data feed execution reports have been collected for the multilateral trading facility (agency broker dark pool) Liquidnet Europe Limited. They incorporate information on the execution's date and time as well as the traded volume and price. Because of Liquidnet's anonymous negotiation mechanism, no information is available whether an execution has been triggered by a buyer or seller. Second, for a valid indication of the traded instrument's true value (benchmark prices) we resort to the home markets principle in Europe (Schwartz and Francioni 2004), i.e. that the instrument's home market is the most liquid one. Therefore, snapshots of the instrument's home market's electronic order book are collected. They are made of the first ten quoted limits and volumes on both sides of the book, i.e. the ten highest bid and ten lowest ask limits. Each change within these limits results in a update record. From these the latest order book situation is selected, which is valid at the reported time of the Liquidnet execution. Regarding our research approach, the order book data lacks secured information on volatility interruptions. This limitation requires to be dealt with during the data selection below.

Table 21 aggregates the properties of these 3,448 executions: First of all the high trade values are striking. For a comparison to typical order book executions table 22 provides an overview of large-, medium- and small-cap instruments traded at the XETRA system of Deutsche Börse Group in 2009. In comparison to those executions the value of Liquidnet trades is about 475 times larger. Average Liquidnet execution values are also considerably higher than trades qualified as large compared to the Normal Market Size (NMS), i.e. 500,000€ for highly liquid stocks (CESR 2008), or compared to the common definition of block trades to exceed 10,000 shares (O'Hara 1995).

Concerning trade frequencies, highly capitalized instruments are the most liquid ones, too. The 63 large-cap instruments account for 57.69% of the trades and even for 76.7% of the execution value. Although medium- and small-caps are traded less frequently, the descriptive statistics indicate their executions to be even more favorable. Whereas for large-cap instruments only 46.41% are trades at the midpoint for mid-caps 64.15% and for small-caps even 69.15% of the trades are executed at this price. For executions within the best bid/ask limit prices (inside market), these proportions persist. Thus, at Liquidnet 96.19% of small-cap trades are priced inside market.

Altogether, the descriptive statistics indicate that finding counterparties for a given trade intention appears difficult: During the 15 months we have analyzed, 3,448 trades for the 192 DOW JONES EURO STOXX constituents have been observed only. However, since 86.75% of the Liquidnet executions are being priced inside market and even 54.9% correspond to the home market's midpoint, Liquidnet executions appear beneficial.

6 Research Hypotheses and Empirical Results

In our research, we aim at exploring the case of Liquidnet as an example of the success story of dark pools in recent years. This analysis should provide insights into the benefits gained by institutional investors when accessing these new trading venues by adopting the required IT, which enables access to these venues. To assess these benefits, it is of major interest if agency broker dark pools provide better executions compared to the home market, at which a share is traded most frequently. To

Market Capitalization	Traded Instrument	Trades	Cumulative Value [m€]	Average per Trade		Executions at / within	
				Shares	Value [€]	Midpoint	Inside Market
Large	63	1,989	6,627	163,651	3,331,745	46.41%	81.13%
Medium	60	882	1,476	122,269	1,670,607	64.74%	92.74%
Small	51	577	537	74,434	930,471	69.15%	96.19%
All	174	3,448	8,641	138,136	2,504,504	54.90%	86.75%

Table 21: Liquidnet Trading Data Sample Characteristics

Market Capitalization	Index	Trades	Cumulative Value [€]	Average Value [€] per Trade
Large	DAX	104,465,966	732,661	7,013
Medium	MDAX	27,690,194	78,143	2,822
Small	SDAX	3,118,248	4,729	1,516
All		135,274,408	737,390	5,451

Table 22: Xetra Execution Statistics for 2009 (Source: Deutsche Börse Group)

address this question, we aim at benchmarking executions observed at Liquidnet by applying our introduced conceptual model on benchmarking securities trading price improvements. With observing and comparing the outcome of IT-supported securities trading processes, we follow an approach with a focus on post-implementation IT benchmarking (Doll et al. 2003). As a first research hypothesis, we address the question if significantly price improvements can be shown for Liquidnet executions observed (H1):

H1: *The average relative price improvement of Liquidnet executions is positive.*

Statistically, H1 is explored by the following null hypothesis $H1_0$, which we aim to reject in the following.

$H1_0$: $\mu(\textit{relative Price Improvement}) \leq 0$

For the 3,448 Liquidnet executions observed, we have calculated the corresponding relative price improvements. Descriptive statistics for these *relative PIs* are provided in table 23. Furthermore, the calculated t-statistic provides evidence that significant relative price improvements can be observed.

	Observations	Mean [bps]	Median [bps]	Std. dev. [bps]
relative PI	3,448	5.1343	3.4142	15.6712
t-Value ($H1_0$)	19.2381^{***}			

Table 23: Price Improvement Sample Characteristics and Test Results

After showing that investors accessing Liquidnet can realize significant price improvements compared to the standard process of trading at the security's home market, we aim at further analyzing the determinants of these price improvements. Therefore, we aim at exploring trade characteristic, which most significantly lead to these price improvements.

First, we have a focus on trade sizes and therefore aim at comparing price improvements of block trades and non-block trades. According to the classification of trade difficulty by (Kissell et al. 2003), we define block trades as those exceeding 15% of the respective instrument's average daily volume (ADV) of the last 30 trading days. Such trades can be expected to take multiple days to be completed at traditional exchanges. Further, such large block trades should trade at *"worse"* prices (O'Hara 1995). We consequently formulate our second hypothesis which aims at detecting a significant *relative PI* difference between block and non-block trades (H2a)

H2a: *The average relative Price Improvement of block and non-block trades on Liquidnet is different.*

H2a$_0$: $\mu(\textit{relative } PI_{\textit{block}}) = \mu(\textit{relative } PI_{\textit{non-block}})$

	Observations	Mean [bps]	Median [bps]	Std. dev. [bps]
relative PI_{block}	335	11.4229	5.9964	22.6345
relative $PI_{\text{non-block}}$	3,113	4.4576	3.2258	14.5713
t-Value (H2a$_0$)	5.5101***			

Table 24: Block Trade Sample Characteristics and Test Results

Table 24, showing descriptive sample characteristics and the statistical test result, outlines that – on the basis of the definition of block trades applied – trading large blocks via Liquidnet appears most beneficial.

Furthermore, we explore the initiator-side of a trade, for which we expect a significant impact. As pointed out by Kraus and Stoll (1972) for traditional exchanges, *"Blocks are sold, not bought"* (p. 573). Further, arguments for hypothesis H2b are provided by asymmetries in negative price movements (market impact costs), which have been detected for buy and sell orders (Bikker et al. 2007; Keim and Madhavan 1997).

H2b: *The average relative Price Improvement of buy- and sell-inititated trades on Liquidnet is different.*

H2b$_0$: $\mu(\textit{relative } PI_{\textit{buy}}) = \mu(\textit{relative } PI_{\textit{sell}})$

	Observations	Mean [bps]	Median [bps]	Std. dev. [bps]
relative PI_{buy}	791	0.6834	1.2423	10.2736
relative PI_{sell}	765	1.0763	0.5302	18.5995
t-Value (H2b$_0$)	-0.5134			

Table 25: Initiator Side Sample Characteristics and Test Results

As shown in table 25, only 1,556 observations were identified as buy- or sell-initiatied. Since, the remaining executions were executed at the home market's midpoint, they were not included in this analysis. The calculated t-value does not provide any evidence that there is a significant difference between buy- and sell-initiated trades, which contradicts the observations of Bikker et al. (2007) and Keim and Madhavan (1997) for traditional order book trading.

Finally, we explore the impact of market capitalization on relative price improvements using the definition of small-, mid- and large-cap instruments presented in table 21. As shown by Stoll (2001), lower market caps and the accompanied lower liquidity of an instrument can incur higher market impact costs, and therefore, we formulate hypothesis H2c.

H2c: *At least one of the medians of relative Price Improvement for large-, mid- or small-cap instruments differs from the others.*

H2c$_0$: $median(rel\ PI_{large}) = median(rel\ PI_{mid}) = median(rel\ PI_{small})$

Given unequal variances (we rejected the corresponding *Bartlett-Test*), we applied an independent sample Kruskal-Wallis Test (H-Test) for heterogeneous variances.

Table 26 summarizes sample characteristics and test results providing evidence that there is a significant difference between the market capitalization samples and regarding the relative price improvement. This finding and the shown mean values provide evidence that Liquidnet trades of small- and mid-cap shares appear most beneficial compared to prices available at the home market.

	Observations	Mean [bps]	Median [bps]	Std. dev. [bps]
relative PI_{large}	1,989	1.6447	2.4954	8.0207
relative PI_{mid}	882	9.6339	5.8624	22.6266
relative PI_{small}	577	10.3021	7.5629	19.1226
H-Value (H2c$_0$)	645.2694***			

Table 26: Market Capitalization Sample Characteristics and Test Results

7 Summary and Conclusion

The securities trading process has gained much complexity in recent years, also due to an increasing amount of additional market places available. Supporting this process by IT and gaining for example access to additional trading venues requires changes in the trading process and the adoption of new technologies. One such additional venue, which has gained much market share in recent years are dark pools. With the aim of analyzing if adapting processes and adopting new technology can be justified economically, we have explored such a dark pool called Liquidnet and explored the potential benefits it can provide to its customers. Our results provide strong evidence that – under certain conditions – dark pools can provide substantial benefits to investors. One major problem we have identified is that finding counterparties in dark pools appears difficult, implying high opportunity costs. However, actual executions appear beneficial, which we have measured by significant relative price improvements compared to trading at a traditional stock exchange. Further analyses provide evidence that these price improvements increase with the actual order size and are negatively related to market capitalization of the stock traded.

Since this is one of the first empirical studies on the business value of dark pools, there is much room for further research and improvements. As a next step, we aim at further analyzing the determinants of the business value provided, which will provide further explanation of relative price improvements in dark pool trading.

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Appendix

Further Publications

Adoption of IT-Driven Trading Technologies

P. Gomber, B. Ende and M. Gsell
Order Handling of Institutional Investors
In: *Journal of Trading, 4(4), pp. 10–31, 2009*

B. Ende and M. Gsell
Investigating the Buy-Side's Adoption Decision for Technology-Driven Execution Opportunities – An Extension of TAM for an Organizational Adoption Context
In: *European Conference on Information Systems Proceedings (ECIS2008), pp. 262–1273, Galway, Ireland, 2008*

Business Value of Dark Pools

B. Ende and J. Muntermann
Dark Pools of Liquidity in Electronic Securities Trading
In: *BIT - Banking and Information Technology, 11(1), pp. 35–44, 2010*

B. Ende and J. Muntermann
Opacity and Exclusivity in Electronic Securities Trading: The Case of Dark Pools
In: *Multikonferenz Wirtschaftsinformatik Proceedings (MKWI2010), pp. 1897–1908, Göttingen, Germany, 2010*

Business Value of Smart Order Router Technology

B. Ende and M. Lutat
Trade-Throughs in European Cross-Traded Equities after Transaction Costs – Empirical Evidence for the EURO STOXX 50
In: *CFS International Conference: The Industrial Organisation of Securities Markets: Competition, Liquidity and Network Externalities Proceedings, Frankfurt, Germany, 2010*

B. Ende, P. Gomber and M. Lutat
Smart Order Routing Technology in the New European Equity Trading Landscape
In: *Software Services for e-Business and e-Society, IEEE (IFIP) Advances in Information and Communication Technology, 305(1), pp. 197–209, Springer, Boston, 2010*

B. Ende, P. Gomber and M. Lutat
The Economic Value of Smart Order Routing in European Equity Trading
In: *International Finance Conference Proceedings, Hammamet, Tunisia, 2010*

Information Based Clustering

B. Ende and R. Brause
Mutual Information Based Clustering of Market Basket Data for Profiling Users
In: *IEEE International Conference on Tools with Artifical Intelligence Proceedings (ICTAI2007), Vol. 1, pp. 374–382, Patras, Greece, 2007*

Curriculum Vitae

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2002 – 2011:	Investment Technology Analyst, Invesco Asset Management
1999 – 2002:	Software Developer, Skyline-Software

Deutsche Zusammenfassung

Order-Channel Management in Institutional Equity Trading: A Framework for IT-Driven Trading Innovations

Bartholomäus Ende

Kurzfassung

IT-getriebene Handelsinnovationen eröffnen institutionellen Investoren neben der Delegation ihrer Handelsaufträge an Broker alternative Ausführungskanäle. Diese Arbeit untersucht die neue Möglichkeit einer selbstbestimmten Auftragsbearbeitung. Die Analyse ist durch den starken Einfluss auf die Intermediationsbeziehungen im Wertpapierhandel sowie die weite Verbreitung neuer IT-getriebener Handelskanäle motiviert. Um die notwendigen Voraussetzungen für das Einlagern (engl. insourcing) des Handels institutioneller Investoren zu erfassen, wird ein Order-Channel Management (OCM) Framework vorgestellt. Im Vergleich zu traditionellen Intermediärsdiensten wächst dessen Komplexität. Um dem Rechnung zu tragen, wird ein strukturierter Ansatz verfolgt. Für die strategische Betrachtung werden Treiber für die Implementierung eines OCM Frameworks untersucht. Operationales OCM basiert auf einer Analyse des IT-Geschäftswertes ausgewählter Handelsinnovationen. Diese umfasst Technologien wie Smart Order Router, Niedriglatenztechnologie als Erweiterung von bereits existierenden elektronischen Handelskanälen sowie Negotiation Dark Pools als Repräsentanten von alternativen Handelsplattformen. Für alle genannten Handelsinnovationen wird deren Potential zur Schaffung zusätzlichen Geschäftswertes aufgezeigt. Dabei wird deutlich, dass Eintrittsbarrieren bestehen, die eng mit der Größe des Investors verbunden sind. Des Weiteren wird Task-Technology Fit als Haupttreiber für die Einführung identifiziert. Dementsprechend sollen IT-getriebene Handelsinnovationen die Ausführungskontrolle steigern, hohe Anonymität gewährleisten und Flexibilität gegenüber variierenden Dringlichkeiten aufweisen.

Inhaltsverzeichnis

1 Einleitung

1.1 Motivation und Ziel der Arbeit

Intermediation nimmt seit jeher im Wertpapierhandel eine bedeutende Rolle ein (O'Hara 2004), die historisch (menschliche) Broker übernahmen. Diese Aufteilung resultiert aus dem limitierten Zugang zum Börsenparkett (Börsenmitgliedschaften) und der daraus folgenden Begrenzung von direktem Handel zwischen Investoren an Börsen. Dementsprechend ist die Auftragsdelegation an Broker der bevorzugte Handelskanal. Dies führt zu einem ausgelagerten (engl. outsourced) Wertpapierhandel von Investoren.

In diesem Zusammenhang werden Intermediäre, die Dienstleistungen des Wertpapierhandels verkaufen, als Sell-Side bezeichnet. Umgekehrt nennt man Investoren, die diese Art von Handelsdienstleistungen konsumieren Buy-Side (Harris 2003).

Die Implementierung institutioneller Investmentstrategien ist auf die kosteneffiziente Ausführung großer Handelsaufträge (Blockaufträge) angewiesen (Kissell et al. 2003). Leider weist die Ausführung solcher Blockaufträge überproportionale Transaktionskosten auf (Almgren et al. 2005). In Anbetracht steigender Handelsvolumina (Bloomberg 2015) und den Grenzen menschlichen Reaktions- und Verarbeitungsvermögens könnte der Wertpapierhandel institutioneller Investoren die manuelle Auftragsbearbeitung (engl. order handling) durch Intermediäre bereits an seine Grenzen gebracht haben. Jedoch wurde durch die Einführung von Informationstechnologien (IT) bereits in den frühen siebziger Jahren der Weg für elektronische Börsen geebnet (Schwartz und Francioni 2004). Diese Automatisierung des Handels spiegelt die Sichtweise Solow's (1957) wider, der technologische Innovation als einzigen Treiber für ökonomischen Fortschritt sieht. Für den konkreten Fall des Wertpapierhandels waren die Einflüsse nicht nur auf Produktivitätsverbesserungen wie höhere, direkte Durchsatzraten (engl. straight-through processing rates) (Weitzel et al. 2003) beschränkt, sondern führten auch zu neuen, alternativen IT-getriebenen Handelskanälen. Hierbei fasst ein *IT-getriebener Handelskanal* eine oder mehrere notwendige *IT-getriebene Handelsinnovationen*[1] zusammen, die für einen Handelsauftrag ausgewählt wurden, um Buy-Side-Händlern die Suche von Gegenparteien für ihre Ausführung zu ermöglichen.

Die Basis für diese neuen Kanäle bildet der direkte Marktzugang durch sogenannte *Direct Market Access* (DMA) Dienste. Diese Innovation überwindet die Beschränkung von begrenzten Börsenmitgliedschaften durch das Virtualisieren des Marktzugangs mittels der IT-Infrastruktur von Brokern. Dabei stellt DMA sowohl eine kostengünstige (Domowitz und Yegerman 2005) als auch unmittelbare (engl. disintermediated) Handelsmöglichkeit dar. Dies erlaubt der Buy-Side die Kontrolle über ihren Wertpapierhandel zu übernehmen, anstatt sie an externe Sell-Side-Händler

[1] Zur Vereinfachung werden im Folgenden die Begriffe Kanal und Innovation als Kurzform von IT-getriebener Handelskanal und IT-getriebene Handelsinnovation genutzt, soweit nicht anders gekennzeichnet.

zu delegieren. Die Nutzung von reinem DMA durch eigene Buy-Side-Händler stellt die einfachste Form eines solchen neuen Kanals für institutionelle Investoren dar. Basierend auf DMA entwickelten sich weitere kosteneffiziente aber stärker automatisierte Kanäle aus komplementären Innovationen wie dem *algorithmischen Handel* oder dem *Smart Order Routing*. Während die erstgenannte Innovation lediglich die Auftragsbearbeitung von menschlichen Händlern an einer einzelnen elektronischen Börse simuliert, weitet die zweite diese Tätigkeit über mehrere Märkte aus. Darüber hinaus ermöglichte die Elektronisierung von Börsen die Entstehung von *alternativen Handelsplätzen* wie Dark Pools. Diese nutzen innovative Marktmechanismen, die sie mittels proprietärer Software und handelsüblicher Hardware implementieren. Diese Innovation generierte eine neue Möglichkeit für Blockaufträge, geeignete Gegenparteien zu finden. Abbildung 26 illustriert die traditionelle, delegierte Auftragsbearbeitung (oberer Teil) und die neue Option für eine selbstbestimmte und deshalb unmittelbarere Auftragsbearbeitung mittels Adoption von Technologie (unterer Teil).

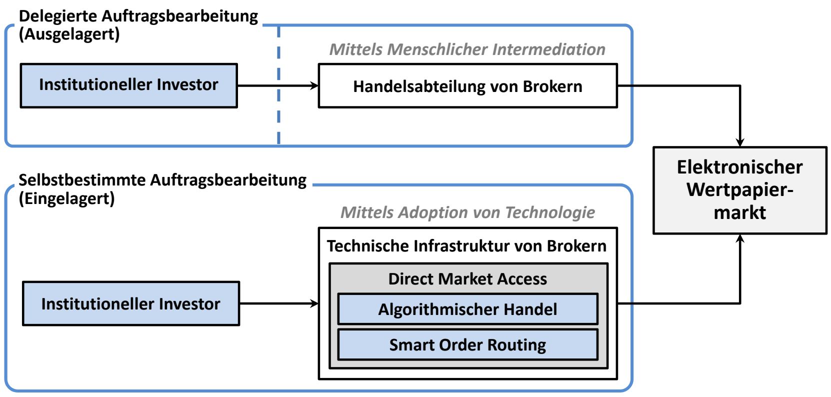

Abbildung 26: Delegierte und selbstbestimmte Auftragsbearbeitung

In der Vergangenheit haben IT-basierte Innovationen weitreichende Veränderungen in den Arbeitsabläufen vieler moderner Industrien angestoßen (Brynjolfsson und Hitt 2000). Trotzdem bleibt die selbstbestimmte Nutzung von neuen Kanälen (*Order-Channel Management*) größtenteils unerforscht. Da ein beträchtlicher Teil der Buy-Side solche Kanäle bereits eingeführt hat (Financial Insights 2006), greift die vorliegende Arbeit diese neuen Handelsmöglichkeiten für institutionelle Investoren auf. Dabei zeigt sie, wie eine verstärkte Nutzung von IT der Buy-Side die Kontrolle über die Implementierung ihrer Handelsentscheidungen erhöhen kann.

Für Buy-Side-Handelsabteilungen bedeutet die Eigenbearbeitung von Aufträgen (engl. inhouse order handling) durch den Aufbau eines Order-Channel Managements (OCM) eine größere Prozesskomplexität. Um dieser Rechnung zu tragen, bietet sich ein strukturierter Ansatz an, der eine Aufteilung in eine strategische und operationale Ebene vornimmt. Dabei beschäftigt sich strategisches OCM mit dem Aufbau einer Eigenbearbeitung von Aufträgen. Der operationale Teil hingegen widmet sich der täglichen Auftragsbearbeitung, d.h. der Zuführung von Handelsaufträgen an zuvor im strategischen OCM ausgewählte und eingerichtete Kanäle.

Motivation des Order-Channel Management Frameworks

Beginnend mit der Jahrtausendwende bieten neue Kanäle institutionellen Investoren erstmals die Möglichkeit, ihre Intermediationsbeziehung zu Brokern zu überdenken. Während die Literatur der Marktmikrostrukturtheorie sich grundsätzlich mit Marktmechanismen und deren Einfluss auf Handelsergebnisse (Hasbrouck 2007) befasst, vernachlässigt sie jedoch das Potential der selbsbestimmten Auftragsbearbeitung. Die überwiegende Mehrheit der Arbeiten untersucht hierzu Preise, Transaktionskosten, Handelsvolumina sowie -verhalten. Ferner befasst sich aktuellere Forschung zur Marktmikrostrukturtheorie mit Effekten einzelner Technologien wie dem algorithmischen Handel, dem Hochfrequenzhandel oder Dark Pools.

Grundsätzlich ist die Literatur hauptsächlich darauf bedacht, isolierte Effekte einzelner Innovationen darzustellen. Die einzige Ausnahme bilden Yang und Jiu (2006), die ein quantitatives Framework für die Algorithmenauswahl vorstellen. Ferner gibt Wagner (2006) vereinzelte operationale Empfehlungen für die Benutzung einiger Handelskanäle. Nichtsdestotrotz besteht eine Forschungslücke in Bezug auf die strategischen und operationalen Entscheidungen, welche von institutionellen Investoren für den Einsatz einer geeigneten Kombination von Kanälen getroffen werden müssen. Deshalb stellt sich die erste Forschungsfrage (FF), und damit der Startpunkt dieser Dissertation, wie folgt dar:

FF1: *Wie kann ein systematischer Ansatz strukturiert werden, der die Nutzung von IT-getriebenen Handelskanälen für institutionelle Investoren beschreibt?*

Strategisches Order-Channel Management

Ursprünglich stammen Innovationen wie der algorithmische Handel aus den Vereinigten Staaten und sind dort für 50% bis 70% des Handelsaufkommens (Carpenter 2013; Treleaven et al. 2013) verantwortlich. Schätzungen für Europa beziffern den Anteil der Handelsaufträge von institutionellen Investoren, die mittels automatisiertem Handel ausgeführt werden, auf 24% bis 43% (ESMA 2014; Grant 2011). Entsprechend ist die Relevanz solcher Technologien auf den Gesamtmarkt unstrittig. Dennoch sind viele institutionelle Investoren weiterhin unschlüssig, ob sie für ihren Handel ein OCM Framework implementieren sollen. Die Marktdurchdringung dieser Art der Auftragsbearbeitung unter großen Investoren wird von deskriptiven Studien wie Gomber et al. (2009) auf lediglich 50% bis 60% beziffert.

Ungeachtet der Bedeutung, welche die Entscheidung von Prozessverantwortlichen zur Implementierung eines OCM Frameworks für den Handelsprozess birgt, fand die Identifikation der darunterliegenden Treiber sowie ihres Zusammenspiels bis dato kaum Beachtung. Lediglich die Technologieadoption von Privatanlegern wurde durch Lai und Li (2005) sowie die von Brokern durch Lucas und Spitler (2000) sowie Khalifa und Davison (2006) untersucht.

Da durch die IS-Literatur die Entscheidungsfindung von Prozessverantwortlichen bezüglich der Adoption von Handelstechnologie bei institutionellen Investoren noch ausgelassen wurde, lautet die zweite Forschungsfrage wie folgt:

FF2: *Welche Faktoren motivieren oder halten Prozessverantwortliche davon ab, ein Order-Channel Management aufzubauen?*

Operationales Order-Channel Management

Nach der Entscheidung für die Implementierung eines OCM Frameworks bedarf ein Prozessverantwortlicher eines Schemas, das individuelle Handelsaufträge geeigneten Kanälen zuordnet (Wagner 2006). Die Basis hierfür stellt eine Methodik bereit, welche die Fähigkeiten von Handelsinnovationen mit den Charakteristika einzelner Handelsaufträge in Einklang bringt (Yang und Jiu 2006). In diesem Zusammenhang spielen geeignete Performancemetriken eine bedeutende Rolle (Hitt und Brynjolfsson 1996).

Leider finden Handelsinnovationen bezüglich der Analyse ihres Geschäftswertes recht unterschiedliche Beachtung, so dass noch nicht für alle Stufen der Wertschöpfungskette geeignete Metriken für die Bewertung von Handelsinnovationen vorliegen. Entsprechend lautet die dritte Forschungsfrage:

FF3: *Welche Performancemetriken ermöglichen Prozessverantwortlichen die Bewertung verschiedener Handelstechnologien?*

1.2 Struktur der Arbeit

Die fünf Paper zur Beantwortung der zuvor genannten Forschungsfragen sind wie folgt strukturiert: **Paper 1** adressiert die erste Forschungsfrage mittels einer eingehenden Literaturanalyse (engl. literature review) sowie Industriescreenings. Aufbauend hierauf wird das OCM Framework spezifiziert, das zudem mittels Experteninterviews evaluiert ist.

Zur Beantwortung der zweiten Forschungsfrage liegt der Fokus sowohl auf Treibern als auch Hemmnissen (engl. inhibitors) bezüglich der strategischen Entscheidung von Prozessverantwortlichen. Diese Art der Fragestellung impliziert klassische Adoptionsforschung, für die eine quantitative Umfrage durchgeführt wurde. Die Studie basiert auf einem in **Paper 2** analysierten Kausalmodel.

Die dritte Forschungsfrage ist operationaler Natur und im Bereich der Forschung über den Geschäftswert von IT (engl. business value of IT) angesiedelt. Für den Wertpapierhandel existiert eine Vielzahl an Innovationen, so dass kaum eine allumfassende Metrik vorstellbar ist, welche die Messung des Geschäftswertes aller Innovationen erfassen kann. Deshalb wurden drei verschieden Technologien ausgewählt. Für jede von ihnen wird eine Methodologie zum Messen ihres Geschäftswertes theoretisch entwickelt und empirisch analysiert (**Papers 3 bis 5**). Die durchgeführten Untersuchungen basieren auf Orderbuch- und Handelsdaten. Für die Bewertung des Potentials von Smart Order Router Technologie (**Paper 3**) wird ein optimaler Router simuliert. Die Simulation umfasst ein Transaktionskostenmodell, um die zusätzlichen Kosten für den Wechsel des Handelsplatzes berücksichtigen zu können. Um die statistische Signifikanz der potentiellen Einsparungen zu quantifizieren, durchlaufen reale Auftragsausführungen diese Simulation. **Paper 4** analysiert das Potential von Niedriglatenztechnologie für deren Einsatz in der selbstbestimmten Auftragsbearbeitung. Die hierfür eingesetzte Simulation ist auf Orderbuchfluktuationen konzipiert, um so die Effekte von Latenz auf die Verlässlichkeit von beobachteten Orderbuchlimitpreisen sowie -volumina zu bestimmen. Abschließend wird in **Paper 5** ein Bewertungsansatz (engl. benchmark) für Negotiation Dark Pools beschrieben. Dieser basiert auf den besten verfügbaren Limitpreisen an traditionellen Börsen und konzipiert ein Model auf deren Basis.

Abbildung 27 bietet einen Überblick zu den verwendeten Methoden und der Gesamtstruktur der vorliegenden Arbeit.

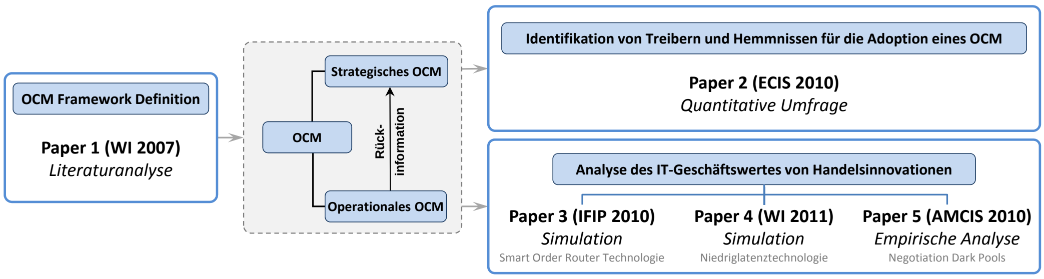

Abbildung 27: Struktur der Arbeit zu Order-Channel Management

2 Forschungskontext: Wie IT-getriebene Handelskanäle die Intermediationsbeziehung der Buy-Side verändern

Zu Beginn dieses Jahrhunderts ermöglichten neue Kanäle institutionellen Investoren neben der traditionellen Intermediationsbeziehung zur Sell-Side die Option einer selbstbestimmten Auftragsbearbeitung. Bei der allgemeinen Analyse dieser und der damit verbundenen Änderung der organisatorischen Struktur muss eine Vielzahl an Faktoren beachtet werden.

2.1 Die traditionelle Delegation der Auftragsbearbeitung

Bis zum Ende der neunziger Jahre war der Wertpapierhandel von institutionellen Investoren komplett an Marktintermediäre ausgelagert. In dieser Zeit bestand die Hauptaufgabe von Buy-Side-Handelsabteilungen in der Auswahl sowie Kontrolle von Brokern, zu denen eingehende Handelsaufträge delegiert wurden. Die Ursache für diese ausgelagerte Form der institutionellen Auftragsbearbeitung ist in der vorherrschenden Infrastruktur begründet. Hierzu zeigt Abbildung 28 die dreigeteilte Struktur der Wertschöpfungskette des Wertpapierhandels (Harris 2003).

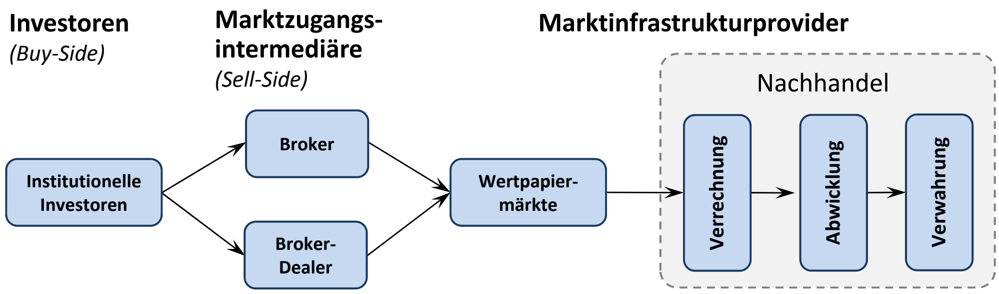

Abbildung 28: Wertschöpfungskette des Wertpapierhandels

Das Hauptmerkmal dieser Wertschöpfungskette besteht in der Intermediation: Statt der direkten Interaktion von Investoren auf Wertpapiermärkten, kontrollieren Broker den Zugang zu regulierten Märkten oder verhandeln Auftragsausführungen außerbörslich (engl. over-the-counter) (OTC). Dies erlaubt gleichermaßen Skalenerträge und Verbundvorteile (Schwartz und Francioni 2004). Dabei profitieren Investoren nicht nur von den Marktkenntnissen der Broker aufgrund deren Spezialisierung sondern auch von positiven Netzwerkexternalitäten, da Broker Zugang zu latenten Handelsinteressen haben (Harris 2003). Darüber hinaus ist der vermittelte (engl. intermediated) Zugang zu Märkten eine kosteneffektive Methode, den reibungslosen Ablauf von Nachhandelsprozessen (engl. post-trading processes) zu organisieren. Anstatt dass alle Investoren vor jeder Transaktion die Möglichkeiten ihrer Gegenparteien zur Erfüllung der bevorstehenden Handelsverpflichtung prüfen müssen, genügt es, dass Broker diese Nachhandelsbedingung für sich und ihre Kunden nachweisen.

2.2 Kritische Betrachtung der delegierten Auftragsbearbeitung

Trotz der Arbeitserleichterungen für Buy-Side-Handelsabteilungen mittels delegierter Auftragsbearbeitung stellt die Intermediationsbeziehung zu Brokern *„das schwerwiegendste Prinzipal-Agenten-Problem der Marktmikrostruktur dar“* (Harris 2003, S. 8).

In diesem Zusammenhang besteht die Hauptsorge der Buy-Side in *Informationsasymmetrien* bezüglich der Bemühungen ihrer Broker, bestmögliche Ausführungen (engl. best execution) zu realisieren. Entsprechend besteht ein stetes Interesse der Buy-Side an selbstbestimmter Auftragsbearbeitung statt der reinen Delegation an Broker. Die Bedenken der Buy-Side resultieren aus der Vielschichtigkeit des Konzepts bestmöglicher Ausführungen, was entsprechend komplizierte Verfahren zu deren Prüfung impliziert (Macey und O'Hara 1997) und somit die Kontrolle von Brokerausführungen erschwert. So müssen geeignete Maße über reine Handelspreise hinaus weitere Dimensionen der Auftragskomplexität wie Volumen und Dringlichkeit umfassen (Kissell et al. 2003). Insbesondere trifft dies auf Handelsaufträge institutioneller Investoren zu, welche zur Suche geeigneter Gegenparteien die Nutzung mehrerer Ausführungskanäle seitens der Broker bedürfen (Wagner und Edwards 1993). Folgt man der Argumentation von Akerlof (1970), so begrenzt sowohl die Nachprüfbarkeit als auch die Unterscheidbarkeit der von Brokern gebotenen Ausführungsleistungen die Qualität[2], die Buy-Side-Handelsabteilungen erwarten können.

Des Weiteren folgt direkt aus den Informationsasymmetrien die Sorge institutioneller Investoren, dass das vertrauliche Wissen bezüglich ihres Auftragsflusses (engl. order flow) von Brokern ausgenutzt werden könnte (Schwartz und Francioni 2004). Eine zwar illegale aber mögliche Praktik besteht im sogenannten *Front Running*. Hierbei profitieren Broker auf Kosten ihrer Kunden davon, dass sie selbst vor ihnen handeln, indem sie dem *Order Exposure Problem* (Harris 2003) zugrundeliegende Effekte nutzen: Grundsätzlich erwarten Märkte, dass Blockaufträge von informierten Investoren ausgehen. Entsprechend reagieren sie auf das bloße Bekanntwerden solcher Aufträge mit negativen Preisbewegungen (engl. market impact). Zusätzliche negative Preisbewegungen resultieren aus dem Ungleichgewicht zwischen Angebot und Nachfrage aufgrund der Ausführung des Blockauftrages. Durch den Nullsummenspielcharakter des Wertpapierhandels (O'Hara 1995) verstärken Broker, die Front Running betreiben, die negativen Preisbewegungen ihrer Kundenaufträge. Dabei handeln solche Broker zunächst auf der gleichen Seite ihrer Kunden, was das Ungleichgewicht von Angebot und Nachfrage verstärkt. Beim darauffolgenden Schließen ihrer Position realisieren sie Preise, die zwar für sie attraktiv sind, jedoch nicht für ihre Kunden.

Um Investoren vor den oben beschriebenen Informationsasymmetrien zu schützen, haben Regulierer Anforderungen an Intermediäre zur bestmöglichen Ausführung eingeführt. Im Fall der Europäischen Union (EU) stellten diese einen zentralen Bestandteil der im November 2007 inkraftgetretenen Richtlinie über Märkte für Finanzinstrumente (MiFID) dar (MiFID 2007). MiFID verfolgt dabei einen prozessbasierten Ansatz, indem Investmentfirmen verpflichtet werden Best Execution Policies einzuführen. Jedoch zeigen Gomber et al. (2012) für den Fall von Deutschland, dass Broker nur Minimalanforderungen dieser Verpflichtung erfüllen.

Für Broker, die neue Buy-Side-Auftragsflüsse zu gewinnen versuchen oder bestehende binden möchten, besteht eine gängige Praktik in *Soft-Commission-Vereinbarungen*. Bezogen auf das OCM der Buy-Side stellen Steil und Perfumo (2003) dar, wie diese Art der Vereinbarungen institutionelle Investoren davon abhalten kann, neue Kanäle zu nutzen. Die Grundlage von Soft-Commissions sind Researchdienstleistungen und Güter wie Infrastruktur, die kostenlos von einem Broker bereitgestellt werden. Im Gegenzug verpflichtet sich die begünstigte institutionelle Investorin, bestimmte Teile ihres Auftragsflusses dem Broker zukommen zu lassen (Schwartz und Francioni 2004). Entsprechend stehen Teile ihres Auftragsflusses nicht mehr für einen selbstbestimmten und potentiell günstigeren Kanal zur Verfügung. Obwohl diese Praktik es Brokern ermöglicht sich von der Konkurrenz zu differenzieren, führt sie eine weitere Dimension des Prinzipal-Agenten-Problems ein: Dabei nehmen jetzt Buy-Side-Unternehmen wie

[2]Verbesserungen der Ausführungsqualität über das nachprüfbare Niveau hinaus können nicht mehr von Qualitäten unterschieden werden, die exakt diese Grenze erreichen. Entsprechend werden Bemühungen von Brokern bessere Ausführungen zu bieten nicht angemessen kompensiert und somit vom Markt verdrängt (Harris 2003).

Fondsgesellschaften die Position des Agenten und Fondsbesitzer die des Prinzipals ein. Für Fondsmanager führen Soft-Commissions zu Interessenskonflikten, da sie die Möglichkeit bieten, Ausgaben aus eigenen Mitteln (Verwaltungsgebühr) auf Kosten von höheren Brokerkommissionen, die direkt aus den Fondsvermögen der Kunden bezahlt werden, einzusparen (Schwartz und Steil 2002). Darüber hinaus zeigt Johnsen (1994) weitere negative Effekte von Soft-Commissions für Handelskosten. So wird gemeinsam mit anderen Forschern wie Livingston und O'Neal (1996) oder Conrad et al. (2001) die Gefahr aufgezeigt, dass der ihnen innewohnende Transparenzmangel Handelskostenmanipulationen ermöglicht und dass Hemmnisse für das Erreichen bestmöglicher Ausführungen bestehen.

Aufgrund ihrer unerwünschten Nebeneffekte stellen Regulierer Soft-Commission Vereinbarungen unter stete Beobachtung. So hatte im Jahr 2006 die britische Finanzaufsicht FCA als erste die Buy-Side dazu verpflichtet, eine klarere Trennung zwischen Zahlungen für Research- und Wertpapierhandelsdienstleistungen einzuhalten (FCA 2013). Einerseits beschränkte die FCA die Art der Dienstleistungen, die durch Brokerkommission abgegolten werden können. Andererseits führte sie auch das Konzept von *Commission-Sharing-Agreements* (CSAs) ein. CSAs basieren dabei auf einer vorab ausgehandelten Aufteilung von Kommissionen. Dabei bekommt der jeweilige Broker einen Teil für seine Auftragsausführung und ein weiterer Teil wird zunächst gesammelt, um danach unter einem oder mehreren, unabhängigen Researchdienstleistern verteilt zu werden. Auf diese Weise kann die Transparenz zwischen den Kosten für die Ausführung und denen für zusätzliche Dienste erhöht werden. Jedoch bedürfen auch Zahlungen mittels CSAs, dass Buy-Side-Handelsabteilungen Teile ihres Auftragsflusses für die Delegation an Broker reservieren. Dies reduziert Skaleneffekte für neue Kanäle und kann so zu einer geringeren Nutzung selbstbestimmter Auftragsbearbeitung führen. Ein Ende dieses Einflusses auf die selbstbestimmte Auftragsbearbeitung ist nicht vor dem Inkrafttreten von MiFID II in 2017 zu erwarten. Grund hierfür sind Vorschläge der European Securities and Markets Authority (ESMA) für eine komplette Trennung (engl. unbundling) der Researchbezahlung von der Auftragsausführung (ESMA 2014). Hierzu schlägt der finale ESMA Bericht für MiFID II vor, Zahlungen für Researchdienstleistungen entweder aus den eigenen Mitteln der Investmentfirma zu begleichen oder aus einem separaten Researchkonto, das den Kunden explizit in Rechnung gestellt wird.

2.3 Entstehen und Folgen von selbstbestimmter Auftragsbearbeitung

In den siebziger Jahren wurde mit der Elektrifizierung von Börsen (Schwartz und Francioni 2004) die Grundlage für das spätere Entstehen von selbstbestimmter Auftragsbearbeitung geschaffen. Die Automatisierung der wichtigsten Börsen dauerte jedoch bis in die neunziger Jahre hinein. Dabei ging mit ihr auch die Verbreitung von elektronischen Limitorderbüchern (e-CLOB) einher (Engelen et al. 2006). Für die folgende Weiterverbreitung von komplementären Innovationen entlang der Wertschöpfungskette bis zur Realisierung von selbstbestimmter Auftragsbearbeitung dauerte es noch einmal bis zum Ende des letzten Jahrhunderts.

Davor profitierte die Sell-Side in vielerlei Hinsicht von automatisierten Märkten. Zunächst erlangte sie DMA, d.h. Broker konnten Aufträge elektronisch an Börsen kommunizieren. Dies erlaubte es ihre Handelsdienstleistungen effizienter bereitzustellen, da sie nicht mehr physisch an Börsen präsent sein mussten. Zudem konnten auf diese Weise Medienbrüche wie Telefonanrufe zu Parketthändlern vermieden werden. Mit der Einführung von standardisierten Kommunikationsschnittstellen zu Börsen wurde dann die komplementäre Innovation von Handelsalgorithmen ermöglicht. Ihr ursprünglicher Zweck bestand in der Erleichterung der täglichen Arbeit der Broker durch eine automatisierte Aufteilung von Handelsaufträgen und der Platzierung resultierender Teilaufträge an einem Wertpapiermarkt. Hierbei schaffen Algorithmen im Vergleich zu menschlichen Händlern Kostenvorteile, wenngleich sie anfangs noch auf einfachere Auftragsgrößen begrenzt blieben (Domowitz und Yegerman 2005).

Vor dem Ende des letzten Jahrhunderts verstärkte die Sell-Side in den Vereinigten Staaten mit dem Ziel von Kostenreduktionen ihre Investitionen in den IT-getriebenen Handel (Goldstein et al. 2009), wodurch die Entwicklung von Innovationen vorangebracht wurde. Treiber hinter diesen Investitionen waren neue Regularien, wie die in 1997 durch die amerikanische Börsenaufsicht (SEC) eingeführten Order Handling Rules oder die in 2001 abgeschlossene Dezimalisierung von Preisänderungen (Harris 2003). Beide Maßnahmen verringerten die Profitabilität der Sell-Side und veranlassten diese Effizienzsteigerungen anzustreben. Darüber hinaus sah sich die Sell-Side gezwungen, ihre bestehenden Einnahmemodelle zu überdenken. Eine Alternative bot sich hierbei in der Konzentration auf stark standardisierte Handelsdienste (engl. low-touch) mit geringen Margen aber Potential für große Umsätze (Goldstein et al. 2009). Da solche Dienstleistungen von Discountbrokern hoher Straight-Through-Prozessraten bedürfen, führte die Sell-Side komplexe elektronische sowie algorithmische Handelsinfrastrukturen für ihre Kunden ein (Khanna 2007).

Zur gleichen Zeit stieg das Bestreben der Buy-Side, ihre Handelskosten zu rationalisieren. Treiber für diese Entwicklung waren Maßnahmen der SEC (SEC 2013) sowie Wettbewerbsdruck aufgrund des Kursverfalls an den Börsen von 2000 bis 2003. Für technologieaffine Buy-Side-Händler boten die neuen Fähigkeiten des algorithmischen Handels, dank der mit ihnen einhergehenden Kostenvorteile, eine willkommene Option auf dieses Umfeld zu reagieren. Bei diesen ersten Schritten auf dem Weg zur selbstbestimmten Auftragsbearbeitung spielten institutionelle Investoren mit hohen Handelsvolumina wie Hedgefonds eine Vorreiterrolle (Khanna 2007). Zu Beginn wurden ihre Entscheidungsmöglichkeiten lediglich um die Wahl zwischen algorithmischen Ausführungsstrategien ihrer Broker erweitert. Jedoch war die Buy-Side recht bald von der, durch die Sell-Side bereitgestellten, Ausführungsqualität und -flexibilität enttäuscht (Investor 2002). Mit dem Ziel die noch beschränkte Handelskontrolle zu verbessern, konzentrierten sich institutionelle Investoren auf Broker-neutrale Möglichkeiten für den Einsatz von Handelsalgorithmen (Opiela 2005; Irrera 2013).

Die technische Grundlage für einen Broker-neutraleren Einsatz von Handelsalgorithmen besteht in der von Medienbrüchen befreiten Verarbeitung von Buy-Side-Aufträgen von ihrer Eingabe in ein Ordermanagementsystem bis zur finalen Ausführung an einem elektronischen Wertpapiermarkt (Khanna 2007). Dieses Straight-Through-Processing beruht dabei auf standardisierten Schnittstellen für die elektronische Weiterleitung von Handelsinstruktionen. In diesem Zusammenhang hat sich das Financial Information eXchange (FIX) Protokoll faktisch zum Standard entwickelt (Aldridge 2010). Die Verbreitung von FIX ermöglichte zur Jahrtausendwende den Einsatz von DMA durch die Buy-Side. Damit ging eine erhebliche Verringerung der Interaktionen zwischen Buy- und Sell-Side einher. Im Prinzip nutzen institutionelle Investoren mittels DMA lediglich die Infrastruktur ihrer Broker, um so deren Marktzugang verwenden zu können. Heutzutage ist DMA ein Synonym für den direkten Zugang zu elektronischen Orderbüchern, der selbstbestimmte Auftragsbearbeitung ermöglicht.

Um von selbstbestimmter Auftragsbearbeitung profitieren zu können, haben Buy-Side-Handelsabteilungen ihre IT-Investitionen gesteigert (Groenfeldt 2014). Diese Ausgaben scheinen sich vor allem für diejenigen institutionellen Investoren ausgezahlt zu haben, die mittels DMA begannen, Algorithmen von unabhängigen Drittanbietern zu nutzen oder sogar eigene Lösungen entwickelten (Investor 2002). Ein Vorteil besteht hierbei in der so geschaffenen Kapazität von Handelsabteilungen die Aufmerksamkeit ihrer (menschlichen) Händler auf komplexe Aufträge (engl. high-touch) zu legen, deren sorgsame Abarbeitung Wert schaffen kann. Zudem ist es für Buy-Side-Händler einfacher mit dem Portfoliomanagement zu interagieren, um so ein besseres Verständnis von der Struktur des Auftragsflusses zu erhalten (Opiela 2005).

Für Handelsabteilungen ist die selbstbestimmte Auftragsbearbeitung gleichbedeutend mit mehr eigenverantwortlichen Entscheidungen. Exemplarisch ist hier die Auswahl von Handelsplätzen zu nennen, deren Wichtigkeit bereits von Battalio et al. (2002) herausgestellt wurde. Während sich die Literatur mit dieser Fragestellung im Kontext amerikanischer Wertpapiermärkte beispielsweise in Bacidore et al. (1999) und Battalio et al. (2001) bereits auseinandergesetzt hat, ist das Phänomen der Liquiditätsfragmentierung für Europa neu. Prinzipiell wurde es durch MiFID initiiert, da diese Direktive verstärkten Wettbewerb unter europäischen Wertpapiermärkten bezweckt. In der Vergangenheit wurde der Großteil des Handels europäischer Wertpapiere auf deren Heimatmarkt abgewickelt, was auch als Heimatmarktprinzip (engl. home market principle) bezeichnet wird (Schwartz und Francioni 2004). Mit MiFID wurden dabei nicht nur Regeln (engl. concentration rules) aufgehoben, die in einigen EU Mitgliedsstaaten den Handel auf nationalen Börsen begrenzten, sondern auch gleiche Wettbewerbsbedingungen mit der Definition von multilateralen Handelssystemen (MTFs) geschaffen. Die auf dieser Basis gegründeten Handelsplattformen wie Chi-X, BATS und Turquoise konnten in kurzer Zeit größere Marktanteile gewinnen (Fidessa 2012). Ein Nachteil dieser Wettbewerbssteigerung besteht in der Liquiditätsfragmentierung, die jedoch mittels Smart Order Routing Technologie begegnet werden kann. Diese Innovation automatisiert Routingentscheidungen und erleichtert damit die Implementierung einer selbstbestimmten Auftragsbearbeitung. Für den Fall von europäischen Wertpapiermärkten müssen jedoch Routingentscheidungen auch die fragmentierte Nachhandelsinfrastruktur (Schaper 2008) berücksichtigen. **Paper 3** greift diese Besonderheit auf und versucht ihren Einfluss auf das Potential von Smart Order Routing Technologie zu zeigen.

Unter Marktteilnehmern des automatisierten Handels können heutzutage unterschiedliche Reaktionsfähigkeiten beobachtet werden. Da zudem mit fortschreitender Komplexität Handelsalgorithmen immer größere und komplexere Teile des Auftragsflusses verarbeiten können, stellt sich für das OCM von Handelsabteilungen zunehmend die Frage nach dem ökonomischen Nutzen einer höheren Reaktionsfähigkeit mittels Niedriglatenztechnologie. In diesem Zusammenhang steht auch das neue Phänomen des Hochfrequenzhandels. Im Gegensatz zum algorithmischen Handel, der eine Möglichkeit für die Implementierung von langfristigen Investitionsentscheidungen darstellt, basiert der Hochfrequenzhandel auf einer Vielzahl von eher kleinen Profiten, die durch häufige Transaktionen generiert werden. Zudem weist Hochfrequenzhandel kurze Haltedauern auf und ist um eine Schließung eingegangener Positionen zum Ende des Handelstages bemüht (Aldridge 2010). Während Niedriglatenztechnologie eine Notwendigkeit für die Wettbewerbsfähigkeit von Hochfrequenzhändlern darstellt, ist ihr ökonomischer Nutzen im Kontext der selbstbestimmten Auftragsbearbeitung für Buy-Side-Handelsabteilungen nur schwer quantifizierbar. Da diese Fragestellung bisher auch von Seiten der Forschung unbeantwortet blieb, versucht **Paper 4** die Bedeutung von Niedriglatenztechnologie für das OCM von Buy-Side-Handelsabteilungen zu beleuchten, indem es den allgemeinen Einfluss von Latenz auf Marktteilnehmer untersucht.

Wenngleich die höhere Transparenz von e-CLOBs zu einer gesteigerten Markteffizienz führt, verstärkt sie im gleichen Maße das Order Exposure Problem für die Buy-Side (siehe Abschnitt 2.2). Dementsprechend sind institutionelle Investoren, deren Blockaufträge die Fähigkeiten von Handelsalgorithmen überschreiten, an intransparenteren Kanälen für ihr OCM-Setup interessiert. Eine solche Alternative für den anonymen Handel bilden Dark Pools (Gresse 2006). Leider weisen diese jedoch eher geringe Ausführungsraten auf (Næs und Ødegaard 2006). Des Weiteren hängen erreichbare Ausführungspreise stark von den verwendeten Marktmodellen ab. Einerseits importieren sogenannte Crossing Networks zu zufälligen Zeitpunkten Preise von vordefinierten Referenzmärkten (Conrad et al. 2003). Andererseits existieren auch Typen dieser Handelssysteme, wie Negotiation Dark Pools, bei denen die Ausführungspreise im Vorfeld unklar bleiben. Aus diesem Grund sind für die erfolgreiche Integration solcher Handelssysteme in ein OCM zwei Kenntnis essentiell: Zum einen ob sie vorteilhafte Ausführungen erlauben und zum anderen welche Bedingungen hierfür erfüllt sein müssen. Zur Beantwortung dieser Fragen entwickelt **Paper 5** einen Bewertungsansatz, der die Analyse dieser Art von intransparenten Kanälen erlaubt.

3 Ergebnisse

3.1 Paper 1[3]: Definition eines OCM Frameworks

Paper 1 erweitert die Literatur zum institutionellen Wertpapierhandel um ein Framework für die selbstbestimmte Auftragsbearbeitung. Ziel dieses Frameworks ist das Aufzeigen einer Möglichkeit für Investoren, wie die Kontrolle der Auftragsbearbeitung gesteigert und gleichermaßen die Abhängigkeit von Brokern reduziert werden kann. Prinzipiell soll so die Effizienz ihres OCMs erhöht werden können. Hierzu ist die Nutzung neuer Kanäle zentral.

Im ersten Schritt wird OCM definiert als *„...der Prozess der Informationsbeschaffung, Bewertung, Entscheidung und Kontrolle bezüglich der Bereitstellung einer Gesamthandelsinfrastruktur (strategisches OCM) und der eigentlichen Implementierung der Auftragsbearbeitung (operationales OCM)“* (Ende et al. 2007, S. 708).

Um das Framework näher zu spezifizieren, werden alle relevanten Entitäten, Parameter, Prozesse sowie ihre Interdependenzen beschrieben. Verglichen mit dem traditionellen Prozess der Delegation zu Brokern, steigert die selbstbestimmte Auftragsbearbeitung die Komplexität einer Handelsabteilung. Abgesehen von den höheren Ansprüchen an die technologischen Fachkenntnisse von institutionellen Investoren, bedarf es Erweiterungen in der Infrastruktur sowie einer Anbindung an eine Vielzahl von Ausführungskanälen. Aus diesem Grund basiert das OCM Framework auf einem strukturierten Ansatz, der einen strategischen und operationalen Teil umfasst:

Strategisches OCM umfasst Managemententscheidungen bezüglich der angestrebten Struktur der Auftragsbearbeitung. Dementsprechend werden Informationen für die Auswahl von geeigneten Handelsplätzen benötigt. Diese beinhalten Merkmale des Auftragsflusses und von Handelskanälen, welche miteinander abgeglichen werden. Hierzu gehören Parameter wie die Gefahr von Informationsweitergabe (engl. information leakage risk), Transaktionskosten, Füllraten, Ausführungswahrscheinlichkeiten sowie die Dringlichkeit des jeweiligen Handelsauftrages. Darüber hinaus obliegt dem strategischen OCM die Bereitstellung aller notwendigen Grundlagen für die Nutzung der gewählten Handelsplätze wie deren Anbindung, Handelssoftware, Händler sowie der technischen Infrastruktur.

Im Grunde befasst sich das operationale OCM mit der eigentlichen Zuweisung einzelner Handelsaufträge zu geeigneten Handelskanälen. Zu diesem Zweck wird ein Klassifikationsschema für fünf Typen von Handelsaufträgen vorgestellt. Dieses basiert auf der Unterscheidung von Handelsaufträgen bezüglich der drei Dimensionen Größe, Gefahr der Informationsweitergabe sowie Ausführungsdringlichkeit. Darüber hinaus bedarf die Umsetzung des operationalen OCM der Fähigkeit, mit Restriktionen von Handelsaufträgen umgehen zu können. Hierfür wird ein Ansatz aus drei

[3] B. Ende, P. Gomber und A. Wranik. An Order-Channel Management Framework for Institutional Investors. In Tagungsbände der internationalen Konferenz Wirtschaftsinformatik (WI2007), Band 2, S. 705–722, Karlsruhe, Deutschland, 2007.

Stufen vorgestellt, der die Schritte der Klassifikation von Handelsaufträgen, der tatsächlichen Kanalauswahl sowie der Reaktion auf deren Realisationen umfasst.

3.2 Paper 2:[4] Adoptionsentscheidung für ein OCM

Die Auswertung einer unter Prozessverantwortlichen der 500 größten europäischen institutionellen Investoren durchgeführten Umfrage ergibt die folgenden drei Hauptergebnisse:

1. Die Entscheidung ein OCM Framework zu implementieren ist primär durch interne Faktoren getrieben. Für die beiden betrachteten externen Faktoren in Form von Wettbewerbsdruck und vertraglichen Hemmnissen kann zwar der erwartete Einfluss auf die Nutzungsabsicht beobachtet werden, jedoch ist dieser relativ schwach. Dagegen erwies sich die Performanceerwartung als der stärkste Indikator für die Nutzungsabsicht. Während sich diese Beobachtung mit Erkenntnissen aus der Literatur zum Technology Adoption Model (TAM) deckt (Venkatesh et al. 2003), kann für den erwarteten Aufwand nur ein eher schwacher Effekt auf die Performanceerwartung gezeigt werden.

2. Die wahrgenommene Übereinstimmung (engl. perceived fit) zwischen den Anforderungen des Auftragsflusses und den Fähigkeiten der Technologie spielen eine zentrale Rolle. Hierbei schafft es TAM nicht, die Effekte von Task-Technology Fit (TTF) vollständig aufzuheben, so dass TTF der stärkste Indikator sowohl für die Performanceerwartung als auch die tatsächliche Nutzung ist. Die Erklärungskraft von TTF bezüglich der Aufwandserwartung ist hingegen schwächer. Nichtsdestotrotz ist die wahrgenommene Eignung einer Technologie sowohl direkt als auch indirekt der Haupttreiber für deren Nutzung. Hierbei bildete TTF innerhalb der internen Faktoren für die Adoptionsentscheidung den Startpunkt einer starken und signifikanten Kausalkette.

3. Die Analyse des formativen TTF-Konstrukts bestätigt die Bedeutung der drei in **Paper 1** bereits vorgeschlagenen Dimensionen zur Klassifikation von Handelsaufträgen. Entsprechend sollten Prozessverantwortliche versuchen, ein besseres Verständnis ihrer wahrgenommenen Übereinstimmung einer Technologie mit den Anforderungen der Handelsaufgabe zu erlangen. Dazu sollten sie ihren Fokus vermehrt darauf legen, inwieweit Innovationen ihre Anforderungen an Kontrolle, Anonymität und unterschiedliche Ausführungsdringlichkeiten erfüllen.

[4] B. Ende. IT-Driven Execution Opportunities in Securities Trading: Insights into the Innovation Adoption of Institutional Investors. In European Conference on Information Systems Proceedings (ECIS 2010), Paper 88, Pretoria, South Africa, 2010.

3.3 Paper 3[5]: Geschäftswert von Smart Order Router Technologie

Paper 3 entwickelt ein Simulationsframework zur Bewertung des Potentials von Smart Order Router Technologie im europäischen Wertpapierhandel, der sich durch eine fragmentierte Nachhandelsinfrastruktur auszeichnet. Zu diesem Zweck werden drei Kostenszenarien entworfen: Keine Transaktionskosten, direkter Zugang (geringe Transaktionskosten) sowie vermittelter Zugang (hohe Transaktionskosten). Die Ergebnisse des letztgenannten Szenarios verdeutlichen, dass lediglich große Investoren mit direktem Handelszugang die Möglichkeit besitzen, das Potential dieser Technologie zu nutzen.

Des Weiteren kann gezeigt werden, dass das Ausmaß vorherrschender, suboptimaler Ausführungen (engl. trade-throughs[6]) sowohl ökonomisch relevant als auch statistisch signifikant ist. Für diese Ausführungen bieten andere Märkte selbst in den kostenbehafteten Szenarien bessere Ausführungspreise. Hierzu werden zunächst die insgesamt 8.010.905 Transaktionen[7] innerhalb eines Szenarios ohne Transaktionskosten betrachtet. Unter dieser Annahme existieren $6,71\%$ (absolut: 537.764) Transaktionen, die anderweitig mit ihrem gesamten Volumen zu einem besseren Preis ausgeführt werden könnten und $6,45\%$ (absolut: 516.797) für die dies zumindest für einen Teil ihres Volumens möglich ist. Dies entspricht innerhalb des Untersuchungszeitraums bereits einem Einsparpotential von 9,50 Millionen Euro. In relativen Zahlen sind dies 7,54bps relativ zu dem gesamten Wert aller suboptimalen Ausführungen bzw. 0,36bps bezogen auf den aller Transaktionen. Selbst für das Szenario des vermittelten Zugangs, der mit hohen Transaktionskosten verbunden ist, verbleibt ein Großteil dieses Einsparungspotentials mit 5,9 Millionen Euro. Jedoch werden bei dieser Betrachtungsweise nur $1,41\%$ der Ausführungen als vollständige und weitere $1,34\%$ als teilweise suboptimale Ausführungen eingestuft.

Aus Gesamtmarktsicht zeigt das Szenario des vermittelten Zugangs, welcher hohe Kosten verursacht, dass für kleinere Investoren das Einsparpotential von Smart Order Router Technologie durch explizite Transaktionskosten überkompensiert wird. Analysiert man hingegen einzelne Wertpapiere, so ist dies nicht immer der Fall. Aus diesem Grund kann das Auftreten von suboptimalen Ausführungen in Europa nicht allein auf Transaktionskosten zurückgeführt werden. Eine mögliche Erklärung könnte darin liegen, dass ein bestimmter Teil der Investmentfirmen sich weiterhin auf das Heimatmarktprinzip (Schwartz und Francioni 2004) beruft und deshalb ein statisches Routing bevorzugt, das pro Wertpapier alle Aufträge an einen vordefinierten Markt weiterleitet. Für den Fall von Deutschland haben Gomber et al. (2012) bereits ge-

[5]B. Ende, P. Gomber, M. Lutat und M.C. Weber. A Methodology to Assess the Benefits of Smart Order Routing. In Software Services for e-World, IEEE (IFIP) Advances in Information and Communication Technology, 341(1), S. 81–92, Springer, Boston, USA, 2010.

[6]Ein Trade-Through beschreibt eine suboptimale Ausführung, in der ein Handelsauftrag mit einem besseren Preis an einem anderen Markt verfügbar aber nicht Teil der Ausführung selbst war (Schwartz und Francioni 2004).

[7]Resultierend aus Instrumenten des Dow Jones EURO STOXX 50 für vier Wochen aus Ende 2007 und Anfang 2008.

zeigt, dass Investmentfirmen genau diese minimale Implementierung eines statischen Routings präferieren.

3.4 Paper 4[8]: Geschäftswert von Niedriglatenztechnologie

Paper 4 entwickelt einen impliziten Simulationsansatz, um den Einfluss von Latenz auf verschiedene Kunden einer Börse zu messen. Der gewählte Ansatz basiert auf dem Konzept von Orderbuchfluktuationen und leitet so Wahrscheinlichkeiten ab, dass Handelsentscheidungen auf veralteten Marktsituationen beruhen. Grundsätzlich zeigen die Ergebnisse, dass der Geschäftswert von Niedriglatenztechnologie hauptsächlich durch die eingesetzte Investmentstrategie getrieben wird. Für Privatanleger sind dabei die beobachtbaren Preis- sowie Volumeneffekte vernachlässigbar. Im Fall von institutionellen Investoren bedarf es jedoch einer Differenzierung bezüglich der mit ihrer Handelsaktivität verbundenen Profite. Je geringer diese durchschnittlich pro Transaktion ausfallen, desto wertvoller erscheint Niedriglatenztechnologie. Zudem steigt der Einfluss von Latenz konkav mit dem Rückgang des Gesamtlatenzniveaus.

Zusätzlich können die folgenden fünf Aussagen zum Einfluss von Latenz getroffen werden:

1. Bei den beobachteten Änderungen des Orderbuchs treten reine Wechsel der Volumen doppelt so häufig auf wie die von Limits. Dies zeigt, dass Standardmaße wie die Volatilität nicht in der Lage sind, den Gesamteinfluss von Latenz zu erfassen. Als Konsequenz der häufigen Volumenänderungen sind passive Strategien, die auf nicht direkt ausführbaren (engl. non-marketable), da limitierten, Handelsaufträgen basieren wie z.B. das Market-Making besonders stark betroffen.

2. Die Wahrscheinlichkeit $p_{fluc}(x)$ mit einer Latenz von x Millisekunden von einer Orderbuchfluktuation getroffen zu werden, weist ein signifikantes Tagesmuster auf. Dieses hat eine U-förmige Struktur und ist unabhängig von der verfolgten Strategie. Zudem kann ein starker täglicher Abfall um ungefähr 14:30 Uhr beobachtet werden. Bezüglich der Größenordnung von $p_{fluc}(x)$ weisen passive Strategien höhere Wahrscheinlichkeiten auf als aktive, während keine signifikanten Unterschiede zwischen Kauf- und Verkaufsstrategien beobachtet werden können.

3. Das beobachtete Tagesmuster bleibt selbst für höhere Latenzniveaus stabil, da diese nur die Größenordnung von $p_{fluc}(x)$ vergrößern. Dabei hat die Skalierungsfunktion eine leicht konkave Form. Mittels einer loglinearen Regression kann gezeigt werden, dass ein Anstieg der Latenz um 1% die Wahrscheinlichkeit, dass man von einer unvorteilhaften Orderbuchänderung getroffen wird,

[8] B. Ende, T. Uhle und M.C. Weber. The Impact of a Millisecond: Measuring Latency Effects in Securities Trading. International Conference on Wirtschaftsinformatik Proceedings (WI2011), Paper 116, OUTSTANDING PAPER AWARD NOMINEE, Zurich, Switzerland, 2011.

um 0,9% ansteigen lässt. Dies impliziert, dass der absolute Einfluss der Latenz steigt, wenn ihr Gesamtniveau sinkt.

4. Instrumente mit höherer Marktkapitalisierung weisen einen stärkeren Latenzeinfluss auf als geringer kapitalisierte.

5. Bezüglich der durch Latenz induzierten Veränderungen von Limitpreisen und deren Volumen konnte gezeigt werden, dass Limitpreisänderungen über den Handelstag hinweg abnehmen. Für Volumenänderungen hingegen kann kein stabiles Muster beobachtet werden. Ferner zeigen die Ergebnisse für eine exemplarische Hochfrequenzstrategie aus Narang (2010), dass bereits die Kosten von Limitpreisänderungen durch eine Latenz von 50ms zu einer Profitabilitätseinbuße von 26% führen.

3.5 Paper 5[9]: Geschäftswert von Negotiation Dark Pools

Paper 4 entwickelt einen IT-Bewertungsansatz, der Ausführungen eines Negotiation Dark Pools mit Preisen vergleicht, die zeitgleich an traditionellen Börsen realisierbar sind. Auf diese Weise kann für den Fall, dass die Ausführung des Negotiation Dark Pools sich innerhalb der Geld-Brief-Spanne befindet, eine positive Preisverbesserung abgeleitet werden.

Die deskriptive Analyse der Handelsdaten bestätigt die Literatur dahingehend, dass Transaktionsgrößen nach CESR (2008) *„Large in Scale"* sind. Prinzipiell sind Ausführungen auf Liquidnet ungefähr 475-mal größer als vergleichbare Transaktionen auf traditionellen Börsensystemen wie dem deutschen XETRA. Andererseits ist es schwierig passende Gegenparteien zu finden (Harris 2003; Næs und Ødegaard 2006), da die Handelsfrequenz gering ausfällt. So wurden im Beobachtungszeitraum von 15 Monaten zwischen dem 6. Juni 2008 und dem 14. September 2009 durchschnittlich nur 18 Transaktionen für jedes Mitglied des DOW JONES EURO STOXX beobachtet. Dabei ist die Zahl der Transaktionen positiv mit der Marktkapitalisierung korreliert.

Die statistische Analyse führt zu folgenden beiden Einblicken:

1. Die Vorteilhaftigkeit des Handels auf Negotiation Dark Pools kann nachgewiesen werden. Während die durchschnittlichen Kosten durch negative Preisbewegungen für Ausführungen von Blockaufträgen zwischen 20bps für Kauf- und sogar 30bps für Verkaufsaufträge betragen (Bikker et al. 2007), weisen die Ausführungen auf dem untersuchten Negotiation Dark Pool sogar Preisverbesserungen auf. Ihr Medianwert beträgt dabei 3.41bps.

2. Die Untersuchung der Ausführungsmerkmale zeigt, dass Blockaufträge zu signifikant stärkeren Preisverbesserungen führen. Des Weiteren können signifikante

[9] B. Ende und J. Muntermann. Assessing IT-Supported Securities Trading: A Benchmarking Model and Empirical Analysis. Americas Conference on Information Systems Proceedings (AMCIS 2010), Paper 476, BEST PAPER AWARD NOMINEE, Lima, Peru, 2010.

Unterschiede zwischen den verschiedenen Marktkapitalisierungen beobachtet werden. Hierbei zeigen sich insbesondere Ausführungen in klein- und mittelkapitalisierten Werten als besonders vorteilhaft, da diese zu den stärksten Preisverbesserungen führen. Diese Beobachtung unterscheidet sich von Erfahrungen an traditionellen Börsen. Dort führen gewöhnlich niedrigere Kapitalisierungen und die damit einhergehende geringere Liquidität zu höheren negativen Preisänderungen (Stoll 2001). Die Untersuchung der Seite, welche die Transaktion initiiert (Käufer oder Verkäufer) kann keine signifikanten Asymmetrien innerhalb negativen Preisänderungen identifizieren. Dies kann den geduldigeren Händlern auf Negotiation Dark Pools geschuldet sein, während auf traditionellen Börsen *„Blocks verkauft werden und nicht gekauft“* (Kraus und Stoll 1972, S. 573), was zu höheren Preiszugeständnissen für die Verkäuferseite führt.

4 Beitrag zu Literatur und Praxis

4.1 Literaturbeitrag

Die vorliegende Arbeit nutzt Theorien zur Technologieadoption sowie der Analyse des IT-Geschäftswertes. Entsprechend erweitert sie diese Forschungsbereiche um Methoden zur Untersuchung neuer Handelstechnologien. Hierbei werden auch neue Erkenntnisse für die Marktmikrostrukturtheorie gewonnen. Die Beiträge zu jedem Teilgebiet lauten wie folgt:

Technologieadoptionsforschung

In Abgrenzung zu bisheriger Adoptionsforschung im Wertpapierhandel beschränkt sich **Paper 2** nicht nur auf eine einzige Innovation. Ferner wird TAM erfolgreich um zwei Aspekte erweitert: Zum einen wird durch die Zusammenführung mit seinem Vorgängermodel ermöglicht, dass externe Faktoren wie Wettbewerbsdruck und vertragliche Hemmnisse erfasst werden können, zum anderen wird der Vorschlag von Dishaw und Strong (1999) für die Integration von TAM mit TTF empirisch bestätigt. In diesem Zusammenhang stellen die Ergebnisse der **Paper 1 und 2** nicht nur eine formative Formulierung von TTF für die Domäne des Wertpapierhandels vor, sondern testen diese auch erfolgreich. Dabei kann für den gewählten Untersuchungskontext einer arbeitsbezogenen Aufgabe gezeigt werden, dass die wahrgenommene Angemessenheit (engl. perceived fit) einer Technologie den wichtigsten Treiber für deren Nutzung darstellt. Dies geschieht sowohl in direkter als auch indirekter Weise. Hierbei wird deutlich, dass innerhalb der internen Faktoren TTF den Startpunkt einer Kausalkette signifikanter Zusammenhänge bildet.

Analyse des IT-Geschäftswertes

Die **Paper 3, 4 und 5** erweitern die Literatur im Hinblick auf Performancemetriken (Hitt und Brynjolfsson 1996) für Handelstechnologien wie Smart Order Router

(**Paper 3**), Niedriglatenztechnologie (**Paper 4**) und Negotiation Dark Pools (**Paper 5**). Dabei wird in **Paper 3** ein Simulationsansatz eingeführt, der eine Nachverfolgung (engl. tracking) von Verbesserungen der Geschäftsprozesse entlang der gesamten Wertschöpfungskette erlaubt. Die Untersuchung erfolgt in Anbetracht steigender Fragmentierung von europäischen Wertpapiermärkten. Hierbei erweitert die verwendete Methode das Framework von Chircu und Kauffman (2000) zur Gegenüberstellung von potentiellem und realisiertem Geschäftswert einer Technologie um die Domäne des Wertpapierhandels. **Paper 4** stellt eine Möglichkeit zur Simulation des Einflusses von Latenz auf Investmentstrategien vor (Axelrod 2006). Zu diesem Zweck wird die von Clemons (1991) vorgeschlagene Sichtweise eines Investors ohne Zugang zur untersuchten Technologie – solcher zur Verringerung von Latenz – eingenommen. Um den Einfluss von Latenz zu simulieren werden vier Basisstrategien definiert. Abschließend entwickelt **Paper 5** einen IT-Bewertungsansatz für Negotiation Dark Pools, der als Referenz Limitpreise von traditionellen Börsen heranzieht.

Für alle untersuchten Innovationen wird deren Potential zur Wertgenerierung gezeigt. Dabei werden jedoch auch Eintrittsbarrieren deutlich, die eng mit der Investorengröße verknüpft sind. Entsprechend der Theorie zu Wettbewerbsstrategien (engl. competitive strategy) (Porter 1980) ermöglichen solche Barrieren nachhaltige Steigerungen der Profitabilität (Philip et al. 1995).

Marktmikrostrukturtheorie

Paper 3 erweitert die Literatur zur Ausführungsqualität und marktübergreifenden Handel (engl. cross-market trading), deren Fokus auf den Vereinigten Staaten liegt. Im Gegensatz zu Europa ist dort die Nachhandelsinfrastruktur konsolidiert. Dementsprechend können Arbeiten wie die von Bacidore et al. (1999) oder Battalio et al. (2001), die lediglich Ausführungspreise mit quotierten Preisen vergleichen, nur das Szenario ohne Transaktionskosten abdecken. Aufgrund der fragmentierten Nachhandelslandschaft in Europa führt der Wechsel zwischen Märkten zu hohen Transaktionskostenunterschieden. Aus diesem Grund ist ein direkter Vergleich der amerikanischen Studien mit den europäischen Gegebenheiten nicht möglich. Entsprechend integriert der verwendete Simulationsansatz als Neuerung ein Transaktionskostenmodell. Dieses ermöglicht die von der Giovannini Group (2001, 2003) angesprochenen Ineffizienzen aufgrund der Fragmentierung innerhalb der europäischen Nachhandelsinfrastruktur zu berücksichtigen und zum ersten Mal zu quantifizieren. Zusätzlich erlaubt die Gegenüberstellung der unterschiedlichen Kostenszenarien die Messung des Einflusses dieser Ineffizienzen auf die Routingentscheidung. Dabei wird die Bedeutung der Investorengröße auf die Fähigkeit das Potential von Smart Order Router Technologie zu nutzen deutlich. Ferner kann gezeigt werden, dass suboptimale Ausführungen vor Kosten nicht alleine auf Transaktionskosten zurückgeführt werden können.

Paper 4 weist die Untauglichkeit von Standardmaßen der Marktqualität zur Bewertung des Einflusses von Latenz nach. Prinzipiell resultiert diese aus der Nicht-beachtung von Volumenänderung. Da diese doppelt so häufig wie Limitpreisänderungen auftreten, bleibt somit ein wichtiger Aspekt für passive Händler unbeachtet. Als Alternative wird das Konzept der Orderbuchfluktuation eingeführt, das auf der Unzuverlässigkeit von beobachteten Marksituationen basiert. Aus diesem wird eine Performancemetrik abgeleitet, welche die Wahrscheinlichkeit erfasst, von einer nachteiligen Orderbuchänderung aufgrund von Latenz betroffen zu werden. Die empirische Analyse dieser Metrik zeigt, dass diese Wahrscheinlichkeit in einem konkaven, funktionalen Zusammenhang zur Latenz steht. Ferner wird der Einfluss der Latenz sowohl von der eingesetzten Strategie als auch von der Tageszeit beeinflusst.

Paper 5 erweitert die Literatur zu Dark Pools um eine empirische Analyse des Verhandlungsmechanismus von Negotiation Dark Pools. Hierbei wird bestehende Marktmikrostrukturtheorie bezüglich der hohen Transaktionsvolumina auf Dark Pools bestätigt. Jedoch werden auch Unterschiede zu traditionellen Börsen deutlich. Weder können signifikante Preiszugeständnisse für niedriger kapitalisierte Instrumente beobachtet (Stoll 2001), noch Unterschiede zwischen den negativen Preisbewegungen von kauf- und verkaufsinitiierten Ausführungen von Blockaufträgen gezeigt werden (Bikker et al. 2007). Insgesamt wird deutlich, dass trotz des Verhandlungsmechanismus der Großteil der Ausführungen zum Mittelpunkt der Geld-Brief-Spanne (engl. midpoint) getätigt wird. Insofern kann die Nutzung von Negotiation Dark Pools am besten mit der von traditionellen Crossing Networks verglichen werden.

4.2 Praxisbeitrag

Diese Arbeit adressiert primär die bei institutionellen Investoren für den Handelsprozess zuständigen Entscheidungsträger und zu Teilen Marktregulatoren.

Zunächst wird ein Geschäftsprozess dargestellt, der aufzeigt wie neue Kanäle für die eigene Auftragsbearbeitung genutzt werden können statt der Delegation an Broker. In diesem Zusammenhang wird ein OCM Framework in **Paper 1** eingeführt. Seine Konzeption zielt auf eine Steigerung der Handelskontrolle ab. Zu diesem Zweck werden alle relevanten Aspekte für das Design und die Implementierung eines eingelagerten Handelsprozesses definiert. Die strategische Entscheidung für die Implementierung des in **Paper 1** beschriebenen Frameworks wird in **Paper 2** untersucht. Dabei werden allgemeine Empfehlungen zu Faktoren gegeben, die relevant für eine eigene Auftragsbearbeitung sind. Grundsätzlich sollten sich Entscheidungsträger auf die Eignung der Handelsinnovationen für die Anforderungen ihres Auftragsflusses konzentrieren. Besonderes Augenmerk sollte dabei auf den Bedarf von mehr Handelskontrolle, Anonymität und variierende Anforderungen an die Ausführungsdringlichkeit gelegt werden. Investoren, die bereits ein eigenes OCM betreiben, können ihre Entscheidungen ihrer Vergleichsgruppe (engl. peer group) gegenüberstellen. Die **Paper 3 bis 5** bieten Einsichten mit stärkerem Fokus auf das operationale OCM. Diese beschränken sich nicht nur auf Methoden für die Bewertung von Innovationen sondern geben auch Einblicke in ausgewählte Technologien, auf denen die vorgestellten Methoden angewendet werden. Der Simulationsansatz aus **Paper 3** ermöglicht

Investoren den Nutzen von Smart Order Router Technologie zu bewerten. Durch die Anwendung des vorgestellten Simulationsansatzes auf ihren historischen Auftragsfluss und mittels Neuberechnung des entsprechend der eigenen Kosten passendsten Kostenszenarios – entweder einem vermittelten und mit hohen Zugangskosten verbundenen oder einem direkten und damit kostengünstigeren Zugang – können Entscheidungsträger kontinuierlich die Eignung von Smart Order Router Technologie für ihre Handels- und Anbindungssituation prüfen.

Die Messmethoden aus **Paper 4 und 5** unterstützen die Bewertung von Entscheidungsträgern ähnlich zu der aus **Paper 3**. Dabei legen sie jedoch den Fokus auf Niedriglatenztechnologie sowie Negotiation Dark Pools. **Paper 4** konzentriert sich auf typische Eigenschaften von Handelsstrategien, für die eine Latenzverringerung essentiell ist. Zunächst weist diese Art der Handelstechnologie eine höhere Relevanz für passive Strategien wie dem Market-Making auf. Darüber hinaus steigt ihre Bedeutung für Strategien, die nur relativ geringe Profite mit jeder einzelnen Auftragsausführung generieren. Für Strategien, deren Profite aus längerfristigen Investitionen resultieren, scheint diese Technologie hingegen eher vernachlässigbar. Bezogen auf den Fall von Negotiation Dark Pools weist **Paper 5** auf besonders vorteilhafte Auftragscharakteristika hin, wie niedrig kapitalisierte Instrumente und die Nichtexistenz von höheren Preiszugeständnissen für verkaufsinitiierte Aufträge.

Obwohl alle drei untersuchten Innovationen das Potential haben, Geschäftswert zu schaffen, sollten institutionelle Investoren beachten, dass sie zur Realisierung dieses Potentials die folgenden Voraussetzungen bezüglich ihrer Größe erfüllen müssen: **Paper 3** unterstreicht, dass aufgrund der fragmentierten Nachhandelsinfrastruktur in Europa der Nutzen von Smart Order Router Technologie größtenteils auf große Investoren beschränkt ist, die direkten Zugriff auf den Nachhandel des Ausweichmarktes besitzen. **Paper 4** zeigt, dass Niedriglatenztechnologie nur für solche Marktteilnehmer Wert schaffen kann, die eine ausreichend hohe Anzahl von Aufträgen mit relativ geringen und zugleich kurzlebigen Gewinnen generieren. Schlussendlich bestehen die Anforderungen an Handelsaufträge für Negotiation Dark Pools (**Paper 5**) darin, dass diese groß aber nicht dringlich sein müssen, da es schwierig ist passende Gegenparteien zu finden. Ferner müssen Investoren im konkreten Fall von Liquidnet mindestens 500 Millionen US-Dollar an verwaltetem Vermögen aufweisen, da sie andernfalls keinen Zugang zu dieser Art der Handels (engl. liquidity pool) erhalten.

Paper 3 bietet Marktregulatoren wertvolle Informationen für die Überarbeitung von MiFID. Ihnen wird eine Methodik präsentiert, wie die Effizienz der Orderausführung auf den europäischen Finanzmärkten überwacht werden kann. Da ein Hauptziel von MiFID im gesteigerten Wettbewerb unter europäischen Wertpapiermärkten besteht, können Regulatoren die verschiedenen Kostenszenarien nutzen, um nicht nur Rückschlüsse auf vorherrschende Ineffizienzen zu ziehen, sondern auch um deren Ursprung auf den Handels- oder Nachhandelsbereich einzugrenzen.

5 Einschränkungen und Forschungsausblick

5.1 Einschränkungen

Grundsätzlich resultieren Einschränkungen aus methodischen Entscheidungen oder der gegebenen Datenverfügbarkeit:

Bezüglich erst genanntem ist das in **Paper 1** eingeführte OCM Framework lediglich begrenzt testbar. Für die Prüfung seiner Plausibilität wurden dennoch Experteninterviews genutzt. Darüber hinaus wurden die für das Klassifikationsschema vorgeschlagenen Parameter statistischen Tests innerhalb der Umfrageuntersuchung aus **Paper 2** unterzogen. Dennoch basiert das Framework auf einer Literaturanalyse sowie einem Industriescreening von Mitte 2006. Entsprechend ist es auf solche Innovationen beschränkt, die zu dieser Zeit absehbar waren. Ein Beispiel für eine nachträgliche Konkretisierung ist die Analyse aus **Paper 4** zum Einfluss von Latenz, um auch dem Phänomen des Hochfrequenzhandels Rechnung zu tragen.

Bezüglich der Datenverfügbarkeit muss beachtet werden, dass institutionelle Investoren sehr zurückhaltend darin sind Informationen bereitzustellen, die es auch nur ansatzweise ermöglichen, Rückschlüsse auf ihre Investmentstrategien zu ziehen. Grund hierfür ist die Befürchtung, dass andere Vorteile aus ihren Handelsinteressen ziehen könnten (Harris 2003). In **Paper 2** zeigt sich dies in einer Rücklaufquote von 10% (50 aus 500), da viele Prozessverantwortliche argumentieren, dass sie aufgrund von Firmenrichtlinien an keinen Umfragen teilnehmen dürfen. Dennoch entsprechen die Rückläufer mit einer Abdeckung von 33% des verwalteten Vermögens der Stichprobe dem Ziel, die größten institutionellen Investoren abzudecken. Zudem stimmt die Nutzung von neuen Kanälen mit früheren, deskriptiven Studien wie EdHec (2005) und Financial Insights (2005, 2006) überein, so dass keine systematische Verzerrung zu erwarten ist. Folgt man jedoch der Argumentation von Goodhue et al. (2006), so sind Rückschlüsse auf signifikante Pfade aufgrund der geringen Zahl von Rückläufern eingeschränkt. Dies genügt zwar, um das Klassifikationsschema aus **Paper 1** zu bestätigen, jedoch kann keine endgültige Aussage über den Einfluss des erwarteten Aufwands auf die Nutzungsabsicht getätigt werden. In diesem Fall könnte die Diskriminationskraft (engl. power of the test) zu gering gewesen sein.

Die **Paper 3 bis 5** entwickeln und testen Metriken für die Bewertung von ausgewählten Innovationen. Entsprechend sind die Datenzeiträume so gewählt, um die Eigenschaften dieser Metriken und Innovationen evaluieren zu können. Somit gibt es Einschränkungen sowohl in der Anzahl der Instrumente sowie der Länge der Untersuchungszeiträume. In diesem Zusammenhang ist die Verallgemeinerbarkeit der Zahlen aus **Paper 3** durch die stark gestiegene Fragmentierung europäischer Wertpapiermärkte eingeschränkt. Jedoch liegt das Ziel von **Paper 3** in der Untersuchung des Potentials von Smart Order Router Technologie unmittelbar nach Inkrafttreten von MiFID – also einer Zeit mit entsprechend geringer Fragmentierung.

Weitere Einschränkungen betreffen die Präzision des Datensatzes aus **Paper 3**. Einmal haben die Zeitstempel nur eine Genauigkeit von einer Sekunde und des Weiteren sind nur Orderbuchspitzen (engl. level one data) enthalten. Da auch keine Händleridentitäten vorhanden sind, bedarf es verschiedener Annahmen und Abschätzungen für die Transaktionskostenmodellierung. Um daraus resultierenden möglichen Verfälschungen der Ergebnisse vorzubeugen, wurden in der Untersuchung zwei Kostenszenarien (Modellhändler) definiert. Dabei beschreibt ein Szenario eine Ober- und das andere die Untergrenze für mögliche Transaktionskosten. Hierbei werden die einmaligen Installationskosten eines Smart Order Routers außen vor gelassen, da diese bilateral ausgehandelt und somit nicht öffentlich zugänglich sind. Dennoch können Entscheider für eine individuelle Bewertung des Potentials von Smart Order Router Technologie den vorgestellten Simulationsansatz mit ihren Handelscharakteristika und Beschaffungskosten neu durchrechnen.

Genauso wie **Paper 3** basiert die Untersuchung des Einflusses von Latenz aus **Paper 4** auf Momentaufnahmen von Orderbüchern. Aus diesem Grund sind auch hier keine Händleridentitäten verfügbar, die notwendig wären, um einzelne Transaktionen zu Strategien zusammenzuführen. Da der Einfluss der Latenz jedoch von solchen Strategien abhängt, wurde ein einfaches Simulationsmodell basierend auf vier generischen Strategien eingeführt. Während dieser Ansatz generelle Rückschlüsse über den Einfluss der Latenz erlaubt, bedarf eine monetäre Quantifizierung weiterhin des exakten Wissens über die verfolgte Strategie.

Eine weitere Einschränkung besteht darin, dass die Ergebnisse von **Paper 5** auf zwei Annahmen beruhen: Zum einen bezüglich des fairen Preises eines Instrumentes und zum anderen zur initiierenden Seite. Um die Validität dieser Annahmen sicherzustellen und mögliche Verfälschungen der Ergebnisse auszuschließen, sind sie der Marktmikrostrukturtheorie entnommen.

5.2 Forschungsausblick

Mit der Definition des OCM Konzeptes führt diese Arbeit ein neues Forschungsfeld ein. Dabei sind die Veränderungen der Intermediationsbeziehung der Buy-Side, die durch Technologieadoption hervorgerufen werden, noch nicht vollständig abgeschlossen. Entsprechend kann zukünftige Forschung entweder die in dieser Arbeit beschriebenen Analysen fortführen oder diese um gänzlich neue Aspekte im Rahmen des OCMs erweitern:

Ein möglicher Ansatz könnte dabei die Identifikation von neuen Faktoren für die Untersuchung der Implementierungsentscheidung eines OCM Frameworks aus **Paper 2** darstellen. Hierbei sollte versucht werden den erwarteten Aufwand besser zu erklären, da das vorgestellte Modell für diesen nur eine relativ geringe Erklärungskraft aufweist. Auch könnte sich aufgrund der tiefen Eingriffe in den Kerninvestmentprozess (engl. core investment process) durch die Einführung eines OCMs eine Betrachtung von verschiedenen Risikoaspekten, wie von Featherman und Pavlou (2003) oder Gewald et al. (2006) beschrieben, als lohnenswert herausstellen.

Der Simulationsansatz für die Bewertung des Geschäftswertes von Smart Order Router Technologie aus **Paper 3** kann in zweifacher Hinsicht erweitert werden: Einerseits würde ein Datensatz mit Orderbuchtiefe jenseits der besten Limits (engl. level two data) die Analyse vereinfachen, da keine Unterscheidung von partiellen suboptimalen Ausführungen mehr notwendig wäre. Dies würde neben einer Steigerung der Präzision auch die Untersuchung weiterer Routingstrategien ermöglichen. Andererseits könnte die Momentaufnahme von vier Wochen aus **Paper 3** auf eine kontinuierliche Basis überführt werden. Damit könnte eine Analyse von Entwicklungen innerhalb der Wertschöpfungskette des Wertpapierhandels über die Zeit hinweg durchgeführt werden. Hierbei wäre ein interessanter Untersuchungsgegenstand die Entwicklung der Nutzungsraten von Smart Order Routern sowie der Abbau von Handelsfriktionen. Gleichzeitig würde dieser kontinuierliche Ansatz die Basis für Ereignisstudien bezüglich Bemühungen zur Reduktion von Nachhandelskosten bereitstellen.

Eine Fortführung der Untersuchung zum Einfluss von Latenz in **Paper 4** wäre die Verwendung eines erweiterten Datensatzes. Dabei würde die Existenz von anonymisierten Händleridentitäten erlauben, den Einfluss von Latenz in Abhängigkeit von realen Handelsstrategien zu untersuchen. Darüber hinaus könnten Kennzeichnungen (sogenannten Colocationflags) für einzelne Händler, die eine Anbindung mit niedriger Latenz (engl. low latency connection) besitzen, ermöglichen zu verstehen, wie Hochfrequenzhändler mit anderen langsamer angebundenen Händlern interagieren. Auch würde die Hinzunahme weiterer Handelsplätze die Verallgemeinerbarkeit der bereits beschriebenen Ergebnisse erhöhen.

Die in **Paper 5** vorgestellte Bewertungsmethodik für Negotiation Dark Pools könnte durch das Hinzufügen von weiteren alternativen Handelsplattformen erweitert werden. Hierbei wäre ein Vergleich der Transaktionen von Negotiation Dark Pools mit denen eines anderen großen Crossing Networks wie ITG Posit von Interesse. So ließen sich die Handelsergebnisse auf mögliche Unterschiede aufgrund der verschiedenen Marktmechanismen analysieren. Darüber hinaus könnte die Untersuchung um mögliche nachgelagerte Preisreaktionen an traditionellen Börsen verfeinert werden.

Ein weiteres interessantes Forschungsthema könnte der von der Royal Bank of Canada Capital in 2011 eingeführte Typus von Smart Router namens THOR sein. Während die Maxime im Wettrüsten des Hochfrequenzhandles darin besteht, immer schneller zu werden, basiert THOR auf der Verzerrung von Handelssignalen. Hierzu werden einige von ihnen verlangsamt. Dies soll es – vergleichbar mit dem Konzept von Dark Pools – Hochfrequenzhändlern erschweren, Nutzen aus diesen Handelssignalen zu ziehen. Auch dem am 25.10.2013 gestarteten alternativen Handelssystem IEX liegt dieser Ansatz zugrunde (Picardo 2014). Da diese Innovation beinahe alle in dieser Arbeit untersuchten Handelstechnologien miteinander verknüpft, wäre eine Untersuchung der positiven und negativen Effekte auf die Handelsergebnisse von besonderem Interesse.

Ein weiterer Anknüpfungspunkt über die eingereichten Paper hinaus besteht in der Verallgemeinerung des quantitativen Auswahlframeworks von Yang und Jiu (2006). Während ihr Framework ursprünglich auf die Auswahl eines geeigneten Handelsalgorithmus beschränkt bleibt, könnte dieses im Sinne des OCMs um eine Vielzahl weiterer Kanäle erweitert werden. Dabei würde ein solches breiter aufgestelltes System zur Entscheidungsunterstützung (engl. decision support system) es nicht nur ermöglichen, die für die strategische Aufstellung einzuführenden Handelskanäle auszuwählen sondern auch den geeignetesten Kanal für jeden Handelsauftrag vorschlagen können.

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