2010

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

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Journal:	*18th European Conference on Information Systems*
Manuscript ID:	ECIS2010-0286.R1
Submission Type:	Research Paper
Keyword:	E-finance, Electronic value chains, Information technology adoption, Electronic markets

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.

Keywords: E-Finance, Electronic value chains, Information technology adoption, Electronic markets.

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 & 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 & Menkveld 2002). The importance of these higher level technologies is shown by Gsell & 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 & 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 & 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 & 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"* (Venkatesch 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 & Bala 2008): They include knowledge management systems (Money 2004) and outsourcing (Benamati & 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 & 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 & Bala 2008).

In contrast to TAM, which focuses users' beliefs and attitudes, TTF follows a more rational approach. Dishaw & 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 & Thompson 1995). To benefit from the overlapping perspectives of TTF and TAM, Dishaw & 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 & 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 & Li (2005) apply TAM to investigate the retail adoption of internet banking. TAM is also employed by

Lucas & 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 & 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 & Gsell (2008) is shown in figure 1.

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 & Thompson 1995, Cane & 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 & 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 & Spitler 2000). Thus, a TTF construct as proposed by Dishaw & Strong (1999) and employed by Klopping & 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 re-introduced 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 & 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 & 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 (e.g. 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 & Strong 1998). This deteriorates their explanatory power. Thus, Dishaw & 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 favourable 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 & 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 & 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 (Jevaraj et al. 2006). Thus, we hypothesize

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

Ajzen states that most behavior depends *“at least to some degree on such non-motivational factors as availability of requisite opportunities and resources”* (1991, 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 & 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 DATA SET 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 (c.f. Figure 1) is represented by a set of indicators constituting the employed questionnaire (cf. Table 1). 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”* (Diamantopoulus & Winkelhofer 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 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)"* (1998, p. 311). For the employed model (cf. Figure 1 and Table 1) 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 (c.f. Table 1 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 on the right of Table 2. Discriminant validity is assured, too: The inter latent variable correlations are lower than the square root of the AVE (see the diagonal on the left of Table 2). 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 & Winkelhofer 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 1). 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 1). 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 1). 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 & 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 1) 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 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 1.

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 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.

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 1: Indicators and evaluation results for the measurement model

	Effort Expectancy	Contractual Inhibitors	Intention	Performance Expectancy	Competitive Pressure	Usage	AVE	CR	α
Effort Expectancy	0.871						0.758	0.904	0.840
Contractual Inhibitors	0.273	0.844					0.712	0.908	0.880
Intention	-0.369	-0.272	0.976				0.953	0.988	0.984
Performance Expectancy	-0.452	-0.118	0.722	0.860			0.740	0.919	0.883
Competitive Pressure	-0.030	-0.205	0.139	-0.019	0.840		0.706	0.877	0.822
Usage	-0.441	0.128	0.595	0.626	0.195	0.817	0.667	0.857	0.753

Table 2: Left correlations among latent variables and AVE Square Root (shaded cells) are shown whereas on the right AVE, composite reliability (CR) and Cronbach's alpha (α) are depicted

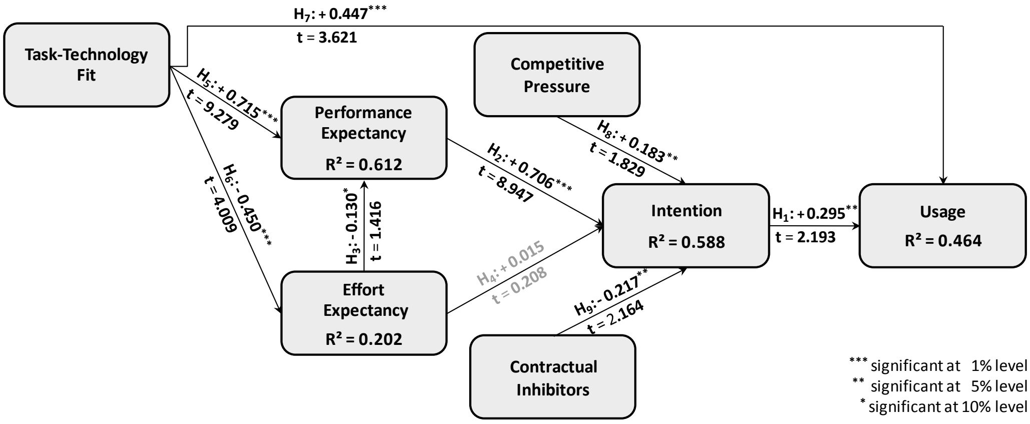

Figure 1. Structural research model with analysis results

5.2 Discussion

In accordance to TAM literature (Venkatesh et al. 2003) performance expectations are the strongest 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 & Strong 1999, Klopping & 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 Goodhue et al.'s (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.

Acknowledgment

We thankfully acknowledge the support of the E-Finance Lab, Frankfurt for this work.

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