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The Impact of IT-Based Trading on Securities Markets

Martin Haferkorn
Goethe-University Frankfurt, Frankfurt am Main, Germany, martin.haferkorn@gmx.de

Kai Zimmermann
Goethe-University Frankfurt, Frankfurt am Main, Germany, kzimmermann@wiwi.uni-frankfurt.de

Michael Siering
Goethe-University Frankfurt, Frankfurt am Main, Germany, siering@wiwi.uni-frankfurt.de

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Martin Haferkorn, Kai Zimmermann, and Michael Siering

Goethe-University Frankfurt, Frankfurt am Main, Germany
{haferkorn,kzimmermann,siering}@wiwi.uni-frankfurt.de

Abstract. The emergence of IT-based trading activities like algorithmic trading or high-frequency trading alters the traditional trading environment within financial markets. Thus, the question arises whether this technological arms race positively affects market quality or represents a risk related to market integrity. Within this study, we evaluate the order-to-trade-ratio for measuring overall IT-based trading activity. Furthermore, in a longitudinal study, we assess the impact of the order-to-trade-ratio on market quality. We find strong indications that price uncertainty has decreased with an increased order-to-trade-ratio and therefore has a positive impact on financial markets. However, the mere upgrade of the trading systems does not relate into increased market liquidity.

Keywords: Algorithmic Trading, High-Frequency Trading, Securities Trading, Order-To-Trade-Ratio, Value of IT

1   Introduction

Measuring the corporate and societal impact of information technology (IT) represents a research topic being highly relevant for several years [1-3]. Whereas many studies argue in favor and against a beneficial impact of IT, related studies are faced with problems concerning the measurement of its impact, the accountability of IT benefits to different areas as well as time lags between IT investments and the resulting effects [4].

In this context, the question of examining the value of IT in general is closely related to the question of measuring the impact of IT on financial markets since this field of interest offers the possibility to overcome the classical problem of measuring IT performance: As typical studies use performance measures based on financial disclosures published in intervals of several months [5], [6], the impact of an increased number of financial market participants using IT in form of algorithmic or high-frequency trading solutions can be measured without time lags by assessing market quality parameters such as volatility and liquidity. Thereby, market participants following highly sophisticated IT-based trading strategies submit and alter orders within very short periods of time, whereas the holding periods of financial instruments decrease [7]. Currently, there is an ongoing discussion whether market participants using these strategies represent a risk for market integrity and exchange infrastructures.

Furthermore, this has lead to the question of how these activities can be measured, how they contribute to market quality and whether these activities have to be limited.

With this respect, several exchanges aim at limiting IT-based trading strategies and introduce fees for high order-to-trade-ratios (OTR), whereas OTR basically relates the number of order submissions to the number of order executions. Thus, market participants following intensive IT-based trading strategies that are connected with an increased number of order submissions and modifications have to pay a compensation for their trading behavior.

Different studies already investigated the impact of IT on financial markets, represented by algorithmic trading and low-latency trading activities [8-10]. However, these studies are confronted with a major problem: either they rely on proxies for these activities and are thus faced with the question whether the applied proxies are appropriate – or these studies rely on datasets that are directly acquired from exchange providers (including a flag for non-human activity) but cover only short periods of time.

Within this study, we want to overcome these issues by combining both approaches: we measure the impact of IT on financial markets by means of OTR, which has also been proposed by different exchanges [11], [12] and is supposed to comprise the key characteristics of many IT-based trading activities. In order to evaluate whether OTR covers IT activity appropriately, we first relate OTR to algorithmic and high-frequency trading activity based on a unique dataset classified by an exchange. We then investigate the relation of OTR and the key financial market quality indicators volatility and liquidity related to the constituents of the German blue chip index DAX for the time period from January 2008 to August 2011 in order to discuss whether IT has a positive impact on financial markets.

The remainder of this paper is structured as follows. Section 2 focuses on related work discussing the IT impact in general as well as the effects of IT on financial markets. Within section 3, we address the problem of measuring the IT activity, whereas section 4 presents the results of our empirical study. Finally, section 5 concludes.

2   Related Literature

2.1   Impact of Information Technology on Firm and Sector Productivity

In general, the impact of IT investments and the following IT usage has been investigated by a variety of studies, e.g. [6], [13], [14]. Basically, these studies relate a measure for IT (e.g. the yearly IT budget per employee) to a firm's performance measure (e.g. the net income per employee or productivity) [5], [6]. Consequently, the impact of IT has been focused on by different studies, whereas IT has been found to have a positive impact on revenue growth of single firms [6], employee productivity levels [5] and to cause a positive spillover effect within connected industries [13]. Furthermore, the importance of supporting factors like complementary organizational resources and the alignment of IT and business strategy have been highlighted [14-16]. However, there are also studies questioning the positive effect of IT on a global

level. For instance, it has been reported that next to increasing IT investments, overall productivity growth has stagnated [17].

In this context, there are several reasons that can be taken into account in order to explain why an increased IT usage may not lead to an increase in productivity. At first, potential advantages of one market participant caused due to IT investments may be canceled out by the same investments conducted by competing market participants [18]. Furthermore, reduced benefits from IT are also attributed to management failure in realizing the potential output and synergies [19].

Apart from these reasons, different methodological aspects can lead to a reduced impact of IT on productivity [4]: One major issue within this context is represented by measurement errors, whereas inputs and outputs are not measured correctly and the IT impact cannot be determined precisely. For instance, different accounting principles hamper the comparability of different firms' financials. Furthermore, the payoffs of IT investments may require some time to be realized, which is not taken into account in related studies. Finally, the positive effects of IT might also be redistributed within firms or misallocated by managers so that they cannot be identified correctly [4].

To overcome these measurement problems and to provide an analysis related to the impact of increased IT application on a global level, we focus on the effects caused by augmented overall usage of computerized trading systems within securities markets. Thereby, market participants apply a variety of IT systems and services, like different algorithms, high-frequency trading solutions or co-location and proximity services that enable them to automatically submit and alter orders within short periods of time. This characteristic has shaped today's trading dynamics significantly as the share of these technologies is still rising. Taking securities' markets into account has the advantage that the market impact of increased technology usage can be measured by observing well-established market quality indicators, i.e. liquidity and volatility. As follows, no further performance indicators have to be constructed. Furthermore, the impact of IT usage can be measured without lags: if market participants upgrade their infrastructure and are able to react faster on emerging situations, this can be measured promptly by an altered order submission behavior. Finally, by combining the benefits of a long-term analysis and a validation by means of a short term dataset which is classified according to the market participants' IT usage, we are able to empirically analyze the co-movement between IT usage and market quality.

2.2 Information Technology Impact on Securities Market Quality

The emergence of IT within the securities trading value chain enabling automation and low-latency trading has significantly influenced trading behavior and dynamics [20]. IT order management and routing systems have offered a competitive advantage to its users and made buy and sell side firms alter their business models to provide connectivity and IT services. But as the majority of market participants are relying on these systems today, the question arises how and to what extent market quality and efficiency has changed through this increase in speed and automation. Alongside the academic studies analyzing certain aspects of securities trading innovations on market efficiency, academics have to overcome a variety of limitations.

Measuring the amount of information technology at financial markets is an ongoing challenge. This is mainly driven by the unavailability of public accessible data allowing distinguishing between human and non-human (automated) traders. As a consequence, research in this field heavily relies on (1) direct observable algorithmic or high-frequency activity reported in proprietary datasets which are provided by exchanges; (2) indirect observable activity based on proxies measured by the analysis of public accessible data. Research with (1) is more accurate but requires an exchange operator willing to provide access to this data, additionally almost every study is limited to a couple of days or weeks through the immense data volume, which bears the risk of biased and time-depended results. (2) is grounded on public data and therefore such a bias can be overcome since studies could cover several years but the results rely heavily on the quality of the proxy or event used to identify a change in IT activity.

For example, [8] received tick data of a temporary fee program introduced by Deutsche Boerse in December 2007, whereby institutions applying automated trading strategies taking part in the program received trading fees rebates. The authors argue that these traders contribute more to the efficient price by placing more efficient quotes. However, the data analyzed covers a total of 13 trading days. [9] assess the introduction of the New York Stock Exchange automated quote dissemination in 2003. The authors provide one of the first event studies dealing with the impact of automated traders on market quality. In this case, the market provider introduced an automated quoting update which enabled faster information transmission for algorithm-based traders that enables an exogenous increase in algorithmic trading and, on the other side, has nearly no advantage for traditional human traders. The authors therefore argue that any change in market quality after this event should be contributed to these automated traders. By analyzing trading characteristics before and after this event, the authors find that algorithmic trading lowers the costs of trading and increases the amount of price information each quote carries. These results are confirmed by [10]: Based on a dataset containing trades being initiated and flagged by algorithms, the authors argue that computers provide liquidity during periods of market stress. Overall these results illustrate that computer-supported traders closely monitor the market in terms of liquidity and information and react quickly to changes in market conditions, thus providing liquidity in tight market situations.

The connection between an increased use of highly automated or low-latency trading systems and higher price variability is highly controversial among academics and politicians. Many studies thereby rely on proprietary data panels, like [21], [22]. Both conclude that it is highly unlikely that these technologies boost price uncertainty. Instead, prices could be considered more stable in times of high algorithmic and low-latency activity. In a simulated approach, [23] creates different market situations with and without the participation of automated traders. [23] identifies decreasing price variability when computers act in the market. Due to reduced trading latency, more orders can be submitted to the market and therefore, the size of each order decreases. Because of smaller order sizes, fewer partial executions occur as the volume in the order book is more often sufficient to completely execute the small order. If less partial executions occur, price movements narrow as an order executes at fewer limits in

the order book. On the other side, [24] indicates that high speed aggressive trading has increased stock price volatility within the years 1995 to 2009 after attributing trading characteristics to different investors. [25] confirm these findings and argue that such strategies could level the risk and magnitude of mispricing and information dispute.

As results vary across studies, datasets and approaches, we are among the first who combine the sufficiency of a long term analysis with a proxy derived from a practical and academic background and validated with a proprietary dataset indicating algorithmic and non-algorithmic activity.

3 Information Technology in Financial Markets

3.1 Academic Approach

Various proxies that are used in related studies identify specific IT innovations (like the amount of algorithmic or high-frequency traders). Most times these proxies are based on the characteristics of the related trading behavior: algorithmic trading as well as high-frequency trading are associated with a high amount of order traffic since related systems allow for quick submission, modification and cancellation of large amounts of orders without human intervention [7]. Therefore, a notable amount of proxies have been proposed to measure this specific behavior to quantify algorithmic trading. [9] Are the first who use "message traffic" as a proxy. They argue that this measure is also used by market participants and market venues, which shall provide evidence for its practical applicability. Due to an increasing trading and message volume, they normalize their proxy by dividing the messages per $100 volume of shares traded. [26] Modify this proxy for their study because of the fact that they are only able to observe best quotes and trades in contrast to all messages as in [9]. [26] Argue that both approaches are very similar and prove this issue by comparing their dataset with [9]. While this concept seems quite straightforward, it should be stated that both proxies are influenced by the market itself. A significant change in price, most notably if the time horizon is long enough, might heavily bias such a proxy, particularly in times of market turmoils. One might argue that there is an influence of the price level on the amount of trading done by algorithms and comparables, but certainly not in such a linear way. Further, the authors do not reveal the composite nor the exact definition of "messages".

A different approach is presented by [27] who take into account typical algorithmic trading strategies which result in so called "strategic runs". These strategic runs are linked messages which are the result of dynamic order placement strategies typically employed by computerized traders. They argue that messages which are observed in small time intervals are linked together and are therefore closer related to non-humans as to humans, especially as humans are not able to react in such a low latency environment. Taking this into account, they conclude that all activity following within the next second of the submission or execution could be algorithm activity. The approach is further refined as only the activity which matches the trading direction and volume

of the submission/execution is classified as relevant. The proxy introduced by [27] might miss activity which does not immediately follow on execution/submission. For example, electronic market maker systems submit orders which might not get executed within the following second. In recent months an increasing awareness to these issues by the market venues could be observed. Consequently the next subsection will show their view and efforts made to identify and limit algorithmic traders.

3.2 Practical Approach

While academia focuses on actively determining the amount of technology at a market-level, exchanges focus on the message-intensive behavior at a client-level. Their key focus is not the actual amount of IT but the massive increase in order messages which stresses the market's infrastructures. Exchanges earn fees when a trade occurs, in contrast to the procession of submission, modification or deletion messages which are not obliged to fees. In fact, a high amount of messages which do not result in an increased amount of executions stresses IT-resources and therefore increases infrastructure costs. The emergence of new technologies such as high-frequency trading further amplified the message-intensive behavior of these traders. As a consequence, several exchanges started to charge for the amount of messages every client submits related to the resulting trades, measured by the OTR. If the OTR exceeds a certain threshold, a fine has to be paid by the market participant for future messages. However, there exist different ways to calculate OTR, as shown by Table 1. In this context, different thresholds and message-types are defined by the exchanges.

Table 1. Current OTR thresholds of Exchanges.

Exchange	Traffic-Type			OTR-Threshold
	Submission	Modification	Deletion	
Boerse Italiana [28]	✓	✓	✓	40 – 100*
Deutsche Boerse [11]	✓	✓	✓	500 – 5000*
EDGX [12]	✓	✓	✓	100
NASDAQ [29]	✓			300

* varies according to the instrument.

As depicted in Table 1, exchanges have a different understanding of which traffic-types should be included to calculate the respective OTR. In particular, all venues take into account the submissions while others focus on modifications and deletion as well. The same applies to OTR thresholds which vary tremendously around different venues. These differences in parameters might be caused by the kind of traders the exchanges want to attract. For example, EDGX focuses on long-term investors rather than algorithmic traders. Therefore, EDGX rewards an OTR lower than six with rebates (e.g. for investment funds) and punishes OTRs higher than 100 with fees [12].

Additionally, German lawmakers consider OTR in their current proposal of the high-frequency trading act ("Hochfrequenzhandelsgesetz"). The law proposed by the

federal ministry of finance is out in place to prevent high volatility market situations. They propose that every exchange has to introduce a self defined OTR threshold. This threshold should be appropriate regarding the key properties of the financial instrument (like liquidity) and the role of the market participant e.g. proprietary traders vs. market makers. With this approach, they seek to minimize the risk of a system breakdown involved by reaching the limit of the exchange's IT-system-capacity [30].

Using OTR as proxy for IT-based trading activities is quite appealing as it captures algorithmic and low-latency trading activity at their key dimensions: massive order traffic-generation with a low amount of trades. Furthermore, it should be noted that this proxy is independent from the price level. On the other side, OTR is not able to capture the entire non-human activity, e.g. algorithms which use market orders or momentum traders would not increase the OTR. However, until now, there has been no study evaluating how good OTR covers non-human market activity.

3.3 Order-To-Trade Ratio and Data Setup

In our study, we use OTR to determine the amount of IT-based trading participation during each trading day. As stated in the previous section, OTR covers the key characteristics of the IT-driven change within securities trading – the growing imbalance within the order traffic activity and the resulting trade executions (Figure 1). The OTR measure is independent from any price level changes possibly influencing various proxies. This is especially important when long time periods are analyzed, as the variability of prices on the long run may result in a variability of a price dependent proxy even though the participation level is unchanged.
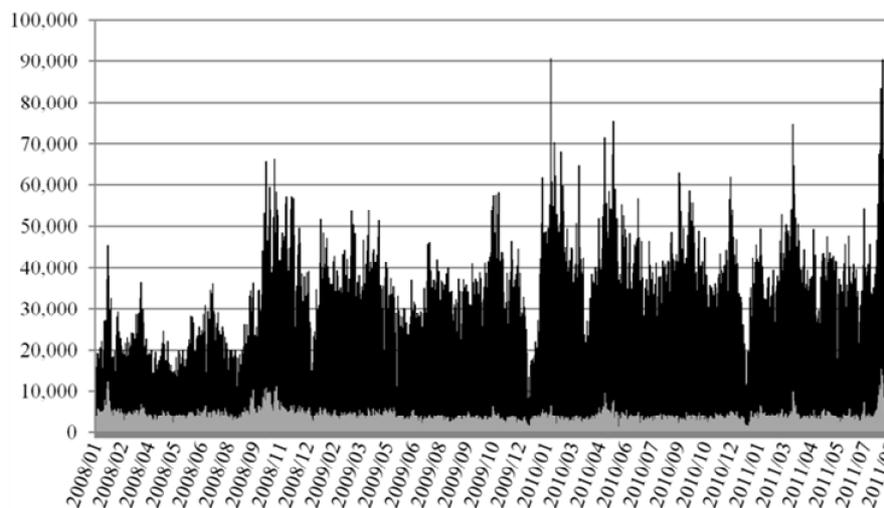

Fig. 1. Medians of daily order submissions (dark) and executions (light) over the DAX 30 constituents from January 2008 until August 2011

For our calculation, we take into account that all exchanges agree that submissions belong to the OTR (see table 1) and therefore, we conclude that a focus on submissions seems to be most appropriate. Figure 1 illustrates the daily median amount of order submissions (dark) and executed trades (light) within the German blue chips. It is evident that next to the seasonal declines in trading activity (December), starting in 2008 the number of submissions has nearly doubled, where the number of executed trades remains fairly stable. This is even more interesting as we consider an instrument-aggregated view. In contrast to the exchanges' client-view, this level of detail captures the daily aggregated OTR including all trading participants within each instrument and thus allows for an assessment of the instrument specific change over time. Moreover, even this level of aggregation confirms the exchange's fear of a massively increased IT overload. Our measure is therefore defined as follows:

$$OTR = (\text{Submissions per Day})/(\text{Trades per Day}) \tag{1}$$

Based on the data of the 30 constituents of the German blue chip index DAX, we aggregate the number of order submissions for each day and each instrument from January 2008 to August 2011 to build a daily panel. We use Thomson Reuters Tick History (TRTH) times and sales data as well as order book situations. Since the submissions are not directly observable in TRTH, we estimate the total number of order submissions by taking into account the increase of the number of orders at each order book level at a tick-by-tick method. OTR is calculated using the daily amount of submissions per reported trades for each DAX 30 instrument.

4   Empirical Study

4.1   Validation of the Order-to-Trade-Ratio

In order to validate our assumptions that the increase in OTR is related to the level of IT-based activity we investigate whether it is capable of distinguishing human from non-human trading activity.

Therefore, we take into account a unique dataset covering the German blue chip index DAX 30 order book activity directly provided by Deutsche Boerse AG. According to [31], Deutsche Boerse AG accounts for about 75% of the DAX turnover within the European lit markets and therefore represents the primary venue for German blue chips. The dataset captures executions, order submissions, modifications and deletions of all German blue chips within a ten day period in March 2009. Next to standard order characteristics, the dataset contains an indication for automated trading activity. This automated trading flag indicates if certain order events were triggered by non-human market participants. The identification is made possible because of a pricing program introduced by Deutsche Boerse AG in 2009, which was offered to institutional investors using algorithmic trading or co-location services. Participants of this trading program had to identify whenever a transaction was generated by an algorithm and in return received a rebate on each submission. Due to this economic incentive we

believe that the identification of algorithmic traders via the automated trading program is the best currently available proxy, further it has been applied and evaluated before by [22].

We calculate a specific daily human and non-human trading OTR based on the unique dataset to show the difference in trading characteristics. Table 2 shows descriptive statistics for both fractions indicating that on average, non-human traders submit ten orders to achieve one execution where, on average, human traders submit only half of the orders to achieve the same amount of executions. Both ratios are stable for the observation period and the null hypothesis, that both ratios decent from the same population can be rejected at high significance levels, as shown by Wilcoxon rank-sum test (Table 2). Interestingly, the correlation between both could only be considered as medium, indicating that human and non-human traders alter their submission to execution behavior non-symmetrically, i.e. react on market signals slightly different.

Table 2. Descriptive comparison of the OTR.

	Non-Human	Human
Mean	10.404	5.489
Median	10.294	5.611
Coefficient of variation	0.0783	0.101
Correlation	0.585	
H_0: Human OTR = Non-Human OTR	$z = 3,780^{***}$	

This observation is in line with findings provided by [7], [9] who found machine message activity to heavily outweigh human activity. However, one may argue that the daily change within the OTR could also be influenced by a systematic change in the underlying ratios. Over the time, human submission activity may have increased tremendously, resulting in an overall increase in OTR without an increased participation of computer traders. Therefore, our further empirical analysis will encompass a limited time window around this data sample. In particular, our time horizon will capture the years 2008, 2009, 2010 and parts of 2011. We assume that within this period a possible change in the basic human / non-human activity level is limited. Foremost, as the human capability to increase its submission activity is limited due to perception constraints, a possible change is more likely originated by non-humans. Within the next section, we present our empirical model and the related results

4.2 Market Quality

While most of the authors focus on a possible increase in excess returns, cost savings or industrial output at company level to assess IT productivity, we focus on possible network effects, i.e. external market effects, due to the increased usage of automated trading participation, measured in OTR. Therefore, we claim that the overall increased OTR alters market quality. Market quality is mostly quantified by the two

key-metrics liquidity and price volatility. Liquidity represents the ability to efficiently meet supply and demand and affects transaction costs for all market participants. Further it is a decisive factor in the competition for order flow among and between exchanges as well as proprietary trading venues [23]. Likewise volatility, a measure for the variability of asset prices, is indicating the level of uncertainty about the true value of the respective asset. High volatility would bias an investor's valuation and potentially resulting in incorrect investment decisions [23].

We address both metrics in order to evaluate possible effects of OTR on securities markets. In order to evaluate different aspects of liquidity and volatility, we use two different measures for each metric. Volatility is measured by the standard deviation of the order book's midpoint, so we account for the average prices' waviness and stability around its mean. To account for the prices' maximum deviation, i.e. the amount of mispricing and overreaction, we use a daily high to low ratio. Following [23], a market's liquidity can be separated in various dimensions. We focus on the daily relative spread as indication for the average implicit trading costs investors face. As market participants demand a compensation for staying in the market, a reduced relative spread may indicate a reduced risk compensation for the traders. Further, we rely on the order book's average depth, i.e. Depth(X). Depth(X) measures the order book thickness X basis points around the midpoint. Traditionally, Depth(X) is denoted in Euro order volume. Since the Depth(X) and the relative spread are highly correlated, as the relative spread determines the amount of orders next to the midpoint particularly if few basis points are chosen, we calculate Depth(X) by excluding the spread and measuring order book depth X basis point around the best bid / best ask. As argued before, we abandon the demotion in Euro volume for the amount of limit orders.

Because of the cross-sectional time series character of our sample we deploy panel regression techniques. This method allows a comprehensive time-sensitive analysis over multiple entities (instruments) and therefore enhances the significance and robustness of our analysis in comparison to ordinary time series analysis. According to [33], the choice between a First Differencing (FD) and Fixed Effects (FE) panel model hinges on the assumptions about the idiosyncratic error term. In particular, the FE estimator is more efficient under the assumption of a serially uncorrelated error term, while the FD estimator is more efficient when the error term follows a random walk. Considering the large time series component of our data structure, we perform a panel regression based on the FE estimator while using the FD estimator for subsequent robustness checks. If FE and FD estimates differ in ways that cannot be attributed to sampling error, violations of the exogeneity assumption can be assumed [33]. Instead, results are considered robust, if FE and FD estimators show consistent results. The error structure is tested to be heteroskedastic, autocorrelated, and correlated between the groups. Driscoll-Kraay standard errors are robust to very general forms of cross-sectional ("spatial") and temporal dependence when the time dimension becomes large. This nonparametric technique of estimating standard errors does not place any restrictions on the limiting behavior of the number of panels [34]. The estimated equation takes the following form:

$$Y_{it} = \beta' X_{it} + \alpha_i + u_{it} \tag{2}$$

The dependent scalar Y captures one of our liquidity or volatility measures, α_i captures the entity-specific intercepts and u_{it} the error term. In line with previous studies like [9] and [26], we include fixed effects for each stock (FD) as well as time and weekday dummies, further we include a couple of control variables as well as the OTR ($1 \times K$ vector X and $\beta \equiv (\beta_1, \beta_2,..., \beta_K)$ is a $K \times 1$ vector). We control for instrument-specific effects via market value, price level, absolute daily return, a couple of dummy variables to capture corporate actions, i.e. equity splits and mergers. To capture the overall growth within the securities trading industry we further add a trend component as well as overall volume aggregates and averages. We include the daily submissions (*Submissions*) and number of trades (*Trades*) in order to eliminate their individual effect and highlight possible effects of OTR. In addition the model is presented without *Trades* and *Submissions* as these variables are implicit part of OTR by definition. Combining OTR and these two variables in one regression might bias the results by generating some artificial correlation amongst the explanation variables. Table 3 illustrates the results of the regression on volatility.

Table 3. Effect of Information Technology on Volatility

| | **Regression on Volatility (FE)** | | | | **High / Low** | | | |
| | **Standard Deviation Midpoint** | | | | | | | |
	β	**T-Value**	**β**	**T-Value**	**β**	**T-Value**	**β**	**T-Value**
OTR	-0.008	-8.47***	-0.006	-4.08***	-0.001	-5.52***	-0.001	-3.21***
Trades	-		0.001	6.25***	-		0.000	9.51***
Submissions	-		0.000	0.87	-		0.000	3.14 ***
Controls	Included		Included		Included		Included	
Trend & Time effects	Included		Included		Included		Included	
Stock effects	Excluded		Excluded		Excluded		Excluded	
Observations	25,500		25,500		25,500		25,500	
Prob > F	0.0000		0.0000		0.0000		0.0000	
Max VIF	4.28		9.42		4.28		9.42	

* / ** / *** significant at 90 / 95 / 99 percent level. For correlation among independent variables, we calculated maximum Variance Inflation Index (VIF) of each model.

The results indicate a persistent relationship between price volatility and the altering OTR. Therefore, volatility, i.e. the standard deviation, as well as the total amount of price over- and undershooting, i.e. the high-to-low ratio, is significantly decreased in times of above average OTR. The results are consistent using the FD estimator (results are not reported here due to space constraints). Keeping in mind that we control for the individual effects of number of trades and number of submissions, the ratio indicates that even an asynchronous divergence of both values, i.e. an increase of the OTR, is accompanied by a lower level of volatility next to the independent effects. The coefficient at number of trades has a positive sign, since the positive relationship between trading activity and volatility was already proven empirically by e.g. [35], [36].

We reuse the proposed model to verify our liquidity proxies, i.e. the relative spread and the depth measures. Again, we include control variables as well as time and trend dummies. Table 4 comprises the results.

Table 4. Effect of Information Technology on Liquidity

	Regression on Liquidity (FE)							
	Relative Spread				Depth (3) ex. spread			
	β	T-Value	β	T-Value	β	T-Value	β	T-Value
OTR	0.000	5.09***	0.000	5.66***	-47.83	-3.26***	9.097	0.67
Trades	-		0.000	1.76*	-		0.531	5.70***
Submissions	-		0.000	-1.58	-		-0.007	-1.18**
Controls	Included		Included		Included		Included	
Trend & Time effects	Included		Included		Included		Included	
Stock effects	Excluded		Excluded		Excluded		Excluded	
Observations	25,500		25,500		25,500		25,500	
Prob > F	0.0000		0.0000		0.0000		0.0000	
Max VIF	4.28		9.42		4.28		9.42	

* / ** / *** significant at 90 / 95 / 99 percent level. For correlation among independent variables, we calculated maximum Variance Inflation Index (VIF) of each model.

Although significant in both models, the results show diverging effects on liquidity. Starting with the relative spread, an increase in the daily OTR is accompanied by a widening of the corresponding relative spreads. Wider relative spreads are equivalent to larger compensation for market participants staying in the market and thus, we do not observe a reduction of this risk premium in times of higher OTR. Foremost, the spread is widening, although the average effect is small. The FD estimator backs this result (results are not reported here due to space constraints). On the other side, the depth measure does not a show persistent relation. As the FD estimator also shows diverting effects, we cannot conclude any relationship between OTR and the order book depth.

4.3 Discussion

We provide empirical insights that the ongoing increase in OTR contributes to changes within market dynamics. The longitudinal analysis indicates that next to the overall growth in trading volumes and prices, the increased usage of algorithms and high speed market access, resulting in increased daily OTR, is related to a decrease in daily market volatility. We observe lower maximum daily price movements as well as lower trade-per-trade price variability at days with high OTR, leading to investor's decisional benefit. Furthermore, we are able to confirm findings of former proprietary data setups indicating that the participation of algorithmic traders is associated with more stable prices for short periods of time, e.g. [22], [23]. Modern IT trading systems and algorithms allow market monitoring and cross-market price observation and offer opportunities to realize small profits. Therefore, the risk of mispricing, represented by an increase of the high-to-low ratio, is heavily reduced as automated sys-

tems eliminate price divergences close to real-time. Further, with the algorithms' ability to submit and keep trades close to the top of the order book, prices become more stable.

Focusing on the regression model for our liquidity measures, results diverge heavily within our models. First, we focus at the order book's relative spread, i.e. the relative difference between best bid and best ask. In fact, our findings suggest that an increase in the OTR is accompanied by wider spreads, although we control for specific order book pattern. Therefore, price stability comes at a price; market participants demand higher compensation for the price monitoring services. Concerning order book depth, we do not observe a persistent relation. The divergence in both models, FD and FE, as well as the divergence through additional control variables indicate endogenity problems possible due to omitted variables. Therefore, a mere technologisation of the trading environment does not boost order book volumes. Further, as our approach does not analyze any causal relationship between the dependent and independent variables, and despite of the various robustness checks, our results have to be further verified carefully before drawing regulatory conclusions. As a consequence, we speak of indications on co-movements rather than causal dependency.

5 Conclusion

The question whether IT has a positive impact on firms or market sectors is challenging academia for several years as it is very hard to measure both: the emergence of IT and the impact it generates. This question is of high relevance specifically in the case of the financial industry where substantial IT investments are made.

Within this study, we analyze the impact of IT-based trading activities on financial markets. Based on academic and practical measures, we identify OTR as an appropriate proxy to capture the key characteristics of the IT driven change within securities trading. We evaluate this measure by means of a proprietary dataset indicating non-human trading activity.

Our contributions are threefold: At first, we provide the first study applying and evaluating OTR in order to measure the amount of IT-based trading. This measure can be used in future research to quantify the amount of these strategies on the basis of public available data. Second, we are among the first who empirically validate OTR with a proprietary dataset which is labeled according to non-human trading activity. Thus, we combine the advantage of applying a reliable measure within a longitudinal analysis. Finally, we consequently provide an indication that IT may have a positive impact on a whole sector. In our case, we find that the share of IT supported trading at a financial market improves price stability but in turn leads to the demand for higher risk compensations.

However, we are aware of the limitation that OTR does not necessarily capture all dimensions of IT-based trading activities. Most obvious, activities leading to order modifications and deletions are not covered by our approach. Further, as the German market system never suffered from a major outage caused by fraud algorithms or low-latency cascades, we would very much highlight that these findings inherit practical

ideality. Therefore, additional markets need to be analyzed to gain further insides. At last, besides of numerous robustness checks, we so far do not evaluate a distinct causal relationship. Therefore, further research is necessary before regulatory conclusions can be drawn.

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