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Algorithmic Trading Engines Versus Human Traders – Do They Behave Different in Securities Markets?

Peter Gomber[1] and Markus Gsell[2]

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Abstract:
After exchanges and alternative trading venues have introduced electronic execution mechanisms worldwide, the focus of the securities trading industry shifted to the use of fully electronic trading engines by banks, brokers and their institutional customers. These Algorithmic Trading engines enable order submissions without human intervention based on quantitative models applying historical and real-time market data. Although there is a widespread discussion on the pros and cons of Algorithmic Trading and on its impact on market volatility and market quality, little is known on how algorithms actually place their orders in the market and whether and in which respect this differs form other order submissions. Based on a dataset that – for the first time – includes a specific flag to enable the identification of orders submitted by Algorithmic Trading engines, the paper investigates the extent of Algorithmic Trading activity and specifically their order placement strategies in comparison to human traders in the Xetra trading system. It is shown that Algorithmic Trading has become a relevant part of overall market activity and that Algorithmic Trading engines fundamentally differ from human traders in their order submission, modification and deletion behavior as they exploit real-time market data and latest market movements.

JEL Classification: D0

Keywords: Electronic Markets, Algorithmic Trading, Order Submission, Securities Trading

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1 INTRODUCTION

IT has triggered a significant transformation in securities trading: The electronification of market venues in Europe, i.e. exchange trading systems like Xetra (Deutsche Börse), SETS (London Stock Exchange) or NSC (Euronext Paris) took place in the late 1990s and enabled market participants (banks, brokers as well as their institutional and retail customers) to access electronic order books via remote access without the need for physical presence on an exchange floor. Now, a second electronic revolution in securities trading is taking place (Preuss 2007): market participants along the value chain started an arms race by automating their trading processes, specifically by applying Algorithmic Trading. Definitions of Algorithmic Trading conceptualize it as the general "use of computer algorithms to manage the trading process" (Hendershot et al. 2008, p.1) or as the "computerized execution of financial instruments following pre-specified rules and guidelines" (Kissel & Malamut 2006, p.12). Gomber & Gsell (2006, p.541) define it as a technology that "emulates a broker's core competence of slicing a big order into a multiplicity of smaller orders and of timing these orders to minimize market impact via electronic means". These algorithms determine ex ante or continuously the optimum volume of the (next) order slice and its time of submission to the market based on mathematical models and considering historical and real-time market data.

For Algorithmic Trading engines, speed of execution, availability of real-time market data and minimum latency have become key success factors as already milliseconds can make a difference. As the speed of data communication is limited by the speed of light, the best option for minimizing latency is to get physically closer to the market. Market operators therefore offer co-location services where market participants can place their trading servers adjacent to the technical infrastructure of the market itself and thus ensure low latency (a latency measurement methodology has been proposed by Budimir & Schweickert (2007)). The downside of this development for market operators is that they have to cope with increasing demands for speed and growing amounts of data and message traffic, i.e. higher investments to upgrade their infrastructure especially for peak loads. The load on market operators' systems is steadily increasing as "Algorithmic Trading is the fastest growing source of order flow" (Preuss 2007, p.154). However, there is only little academic work on how Algorithmic Trading engines schedule their trading strategies and adapt their behavior to current market movements and whether or to which extent it is different to the trading behavior of (human) traders.

Based on a unique dataset that encompasses all order book activity in the 30 most liquid shares traded on Xetra, the electronic trading system of the Frankfurt Stock Exchange, this research aims at demonstrating the manifest differences in the order submission and deletion behavior of Algorithmic Trading engines versus other order flow submitters. This is facilitated as the dataset enables to distinguish between orders submitted by Algorithmic Trading systems and orders submitted by humans. In particular, differences in the order submission strategies and order aggressiveness as well as concerning update/deletion strategies are disclosed. In the following section 2, related work on Algorithmic Trading is discussed. Section 3 gives a brief overview of the underlying Xetra trading system and market model and describes the available dataset. Section 4 presents the results obtained while the final section concludes and gives an outlook on future research in this field.

2 RELATED WORK

Algorithmic Trading systems typically aim at achieving or beating a specified benchmark with their executions and may be distinguished by their underlying benchmark, their aggressiveness or trading style as well as their adaptation behavior (Kissel & Malamut 2006). The volume-weighted average price (VWAP), which is calculated as the ratio of the value traded and the volume traded within a specified time horizon, commonly serves as a benchmark for (automated) trading (Domowitz & Yegerman 2005). The universe of possible strategies has been narrowed down to the efficient frontier of optimal trading strategies (Almgren & Chriss 2000, Almgren & Lorenz 2007). There is evidence that strategies that are adaptive to market developments, i.e. that can vary their aggressiveness, are superior to static strategies (Almgren & Chriss 2000). Furthermore, Algorithmic Trading systems must avoid to be detected as this leaked information could be exploited by other market participants (Brunnermeier & Pedersen 2005). Research on aggressiveness of orders in general is given by Ranaldo (2004) who investigated how (human) traders adapt their behavior to changes in the order book. Empirical research found the execution quality of algorithms to be inferior to executions handled by a broker. Nevertheless, this underperformance can be overcompensated by the fact that algorithms are offered at lower fees than human order handling (Domowitz & Yegerman 2005) as no (expensive) human traders are involved. Due to the increased cost consciousness among market participants, algorithms have become an attractive alternative.

Little research is available that deals with the behavior of Algorithmic Trading systems and their impact on the market itself. Hendershot et al. (2008) showed that Algorithmic Trading has a positive impact on liquidity, while Gsell (2008) found evidence that it has potential to lower market volatility. Datasets similar to the one used for the research at hand have been analyzed by Prix et al. (2007) and (2008). The former analyzes the lifetime distribution of cancelled orders and finds systematic patterns, while the latter investigates cancellation and re-insertion structures in the Xetra order flow. The main distinction to those datasets and the novelty of the dataset used for this research is the information whether an order event was submitted by an Algorithmic Trading system or a human trader.

3 XETRA TRADING SYSTEM AND AVAILABLE DATA SET

3.1 Xetra – The electronic trading system of Deutsche Börse AG

The Frankfurt Stock Exchange, operated by Deutsche Börse AG, has launched the fully-electronic exchange trading system Xetra in 1997. It offers a range of market models that address different asset classes as well as securities with differing liquidity. For high-liquid shares Xetra offers the market model continuous trading. Continuous trading starts after an opening call auction and can be interrupted by one or several intraday call auctions. The trading day ends with a closing call auction.

For securities in the DAX30 index that constitutes the dataset of this research the timing is as follows: At 08:50 the call phase of the opening auction starts. In the call phase, the order book is partially open, as information about the indicative auction price and indicative volume (the volume and price at which executions would take place if the call phase would end instantaneously) or best bid and asks and their volumes are disseminated. Instantly after the end of the call phase, the auction price is determined according to the principle of most executable volume (Schwartz & Francioni 2004). All auction call phases feature a predefined length plus a random end of at most 30 seconds. This means, that for all DAX30 securities the price of the opening auction is determined between 09:00:00 and 09:00:30. After the opening auction, continuous trading starts and for each order immediately upon entry it is checked whether it is executable against orders on the other side of the order book. If no execution is possible or the order was not completely executed, the order is stored in the order book according to price-time priority. During continuous trading the order book is open, i.e. the limits, the accumulated volume per limit and the number of orders per limit are displayed. For DAX30 securities, an intraday call auction interrupts continuous trading at 13:00. After the auction, continuous trading resumes until it is ended by the closing auction which starts at 17:30.

To ensure price continuity, continuous trading may be contingently interrupted by volatility interruptions. In case the next potential price lies outside pre-defined price ranges, a volatility interruption stops continuous trading for an additional unscheduled call auction.

To submit their trading intentions, market participants use market orders or limit orders. Market orders are unlimited buy or sell orders. They are to be executed at the next price determined. Limit orders are buy or sell orders, which are to be executed at their specified limit or better. The buy limit order with the highest limit and the sell limit order with the lowest limit in the order book define the spread of the market. A buy (sell) limit order that is immediately executable due to a limit equal to or higher (lower) than the current best offer (bid) is also called “marketable limit order” as its result equals the result of a market order, i.e. immediate execution. Therefore, market orders and limit orders that trigger immediate executions are called aggressive (or submitted by an aggressor), whilst limit orders that are not immediately executable and that are positioned in the order book are called non-aggressive (or submitted by a non-aggressor). An iceberg order is a hidden order type specified by a limit, an overall volume and a peak volume. The peak is the visible part of an iceberg and is introduced into the order book according to price-time priority. In continuous trading, as soon as the peak has been completely executed and hidden volume is still available a new peak is entered into the book. In auction trading, iceberg orders contribute with their overall volume. Furthermore, market-to-limit orders can be applied, but they are seldomly used and therefore not relevant for the analysis below (for further information on order types and the market model for equity trading see Deutsche Börse 2004).

3.2 Properties of the dataset

The blue-chip index DAX30 comprises the 30 largest and most actively traded companies that are listed at the Frankfurt Stock Exchange. For these securities in 2007, 98% of the order book turnover on German Exchanges was executed on the Xetra trading system (Deutsche Börse AG 2007). The dataset provided by Deutsche Börse AG encompasses all Xetra order book events for the DAX30 securities within the week from October 8th to 12th, 2007 comprising of in total 9,036,638 events and 593,857 trades with an overall value of 33,094,131,632.72 € in continuous trading and in auctions. For each single order book event a code is given that specifies the type of event that occurred. 46.6% of the events are order insertions, 0.9% are modifications, 34.6% are deletions (the number of modifications is low compared to the number of deletions because in the Xetra trading system only a reduction of the order’s volume leads to a modification event retaining the time-stamp as it does not affect price-time priority, while all other changes in order parameters are mapped to a deletion event and a subsequent submission event of a ‘new’ (the modified) order applying a new timestamp). 11% of the events are full executions and 5.9% represent partial executions. The remaining 1% consist of other primarily technical events that are not relevant for the analysis. Each event is assigned a timestamp, identifiers for the affected securities and orders, characteristics of the order and event-specific fields, e.g. a price for an execution. The given timestamps have a precision of 1/100 second.

What makes the available dataset unique is an additional flag in the data that indicates whether the submitter of the order event has been an algorithm. As an order can only be modified by the submitter, all events corresponding to the same order will have the same flag, i.e. an order is either an Algorithmic Trading order or not. Deutsche Börse AG offers a special pricing model, the so-called *Automated Trading Program (ATP)*, which charges a lower fee for automated trading. The exchange defines ATP transactions as “all transactions that have been generated by an electronic system of either the ATP member or the ATP member’s clients, whereby the electronic system has to determine two out of the three following order parameters: price (order type and/or order limit where applicable), timing (time of order entry) and quantity (quantity of the order in number of securities)” (Deutsche Börse AG 2008, p.1). In this program, depending on the accumulated monthly ATP volume per ATP member, a marginal rebate of up to 60% of trading fees applies. To qualify for fee reductions offered by ATP, a member’s trading process has to fulfill some prerequisites. The thereby generated orders have to be channeled directly into the Xetra system without further manual intervention. To enable the application of lower trading fees the ATP orders furthermore must be submitted using a designated ATP Trader-ID. All order events that were submitted using such an ATP Trader-ID are tagged in the available data set. As the tag is anonymous it just gives the information whether this order event is an ATP event or not. It is not possible to pin down behavior to a specific ATP Trader-ID or to directly determine whether two different orders have been submitted by the same market participant or not.

The requirements set by Deutsche Börse to qualify for ATP shall ensure that the users are machines, i.e. Algorithmic Traders. However, it cannot be ensured that vice versa all machines make actually use of the ATP fee rebate, i.e. an event not flagged as an ATP event (in the following: Non-ATP) may still have been submitted by an algorithm. Though, given that the lower fees of ATP constitute a truth-telling incentive for market participants, one can assume the accuracy of the ATP flag to be very high.

4 RESULTS – STRATEGIES OF ALGORITHMIC TRADING ENGINES VERSUS HUMAN TRADERS

The analysis targets at comparing the trading strategies of Algorithmic Trading engines and human traders in several dimensions and to answer the following research questions in this context:

1. *What is the **overall extent** of Algorithmic Trading activity relative to human traders' activity?*
2. *Does Algorithmic Trading activity, i.e. do actual orders submitted by Algorithmic Trading engines, reflect their technical ability to monitor and exploit real-time market movements and market information when algorithms **execute orders aggressively**?*
3. *Does Algorithmic Trading activity, i.e. do actual orders submitted by Algorithmic Trading engines, reflect their technical ability to monitor and exploit real-time market movements and market information when algorithms **position non-aggressive orders** in the order book?*

The focus for the analysis of the research questions is laid on the continuous trading phases as auctions with their call phases of up to ten minutes without any executions exhibit a different trading behavior. The volumes executed in auctions would distort the time-series analysis as they concentrate large execution volumes at a single point of time. Within the dataset 13.4% of overall executed shares (volume) are executed in call auctions, representing 14.0% of the total traded value (in €). These figures include call auctions triggered by volatility interruptions. Within the observation period, five volatility interruptions occurred in different securities executing a total of 46,068 shares representing less than 0.01% of the overall value traded. The analysis of Algorithmic Trading behavior in auctions will be subject to future research. Therefore, the results presented here refer to continuous trading that represents 97% of the overall trading time.

Research question 1: *What is the **overall extent** of Algorithmic Trading activity relative to human traders' activity?*

The activity of ATP traders can be analyzed from two perspectives. On the one hand there is the sheer amount of events (traffic on the electronic trading system) that can be analyzed comparing ATP and Non-ATP events. On the other hand, the focus may be laid on the actual executions by algorithms, i.e. the trading activity, rather than on the mere technical events. Table 1 summarizes the events (see the first two columns for ATP and Non-ATP) and actual executions (see columns 3 to 6 for ATP and Non-ATP) occurring during continuous trading per security. It shows that Algorithmic Trading constitutes a relevant part of overall system traffic and also of actual trading activity. In the observation period, the overall share of ATP events is 52.3% and for only five out of the 30 securities the share of ATP events is below 50%. *Fresenius Medical Care* with 69.0% has the highest rate of ATP events while *Volkswagen* has the lowest rate (35.8%). Concerning the actual execution events, i.e. partial or complete executions, ATP has a share of 54.7% whereby *Linde* has the highest rate of ATP execution events with 65.0% while *Deutsche Telekom* has the lowest with 42.9%. The value associated with ATP trading is 43.0% on average for all securities. As execution events are considered in Table 1, the traded value is double-counted; once for the buyer and once for the seller. 52.7% of the orders entered during continuous trading are ATP orders. ATP and Non-ATP submission exhibit a similar share of aggressive orders (ATP: 14.6%; Non-ATP: 11.2%) (order data not shown additionally in Table 1 to assure readability).

Instrument	ATP						Non-ATP					
	Events	Share	Execution Events	Share	Value (€)	Share	Events	Share	Execution Events	Share	Value (€)	Share
Adidas	91,795	52.6%	15,899	54.6%	308,233,612	41.9%	82,882	47.4%	13,195	45.4%	427,326,823	58.1%
Allianz	292,196	52.3%	43,208	59.6%	1,455,589,385	48.9%	265,999	47.7%	29244	40.4%	1,519,450,139	51.1%
BASF	172,465	59.3%	30,156	62.2%	889,758,389	50.4%	118,232	40.7%	18,317	37.8%	873,992,035	49.6%
Bayer	172,201	57.5%	37,073	56.4%	989,237,021	42.8%	127,413	42.5%	28,687	43.6%	1,322,668,847	57.2%
BMW	106,861	50.7%	19,722	53.5%	444,371,422	43.6%	103,943	49.3%	17,168	46.5%	575,778,930	56.4%
Commerzbank	126,099	46.1%	27,922	45.9%	742,364,567	32.9%	147,673	53.9%	32,944	54.1%	1,515,616,370	67.1%
Continental	114,421	58.5%	18,541	51.8%	401,969,476	39.2%	81,009	41.5%	17,257	48.2%	624,100,587	60.8%
Daimler	258,604	50.1%	52,263	55.8%	2,151,416,279	46.0%	258,018	49.9%	41,379	44.2%	2,523,922,161	54.0%
Deutsche Bank	267,273	53.4%	41,985	52.6%	1,594,711,428	42.4%	233,233	46.6%	37,905	47.4%	2,163,379,719	57.6%
Deutsche Börse	133,699	49.1%	31,833	55.5%	960,562,420	43.2%	138,387	50.9%	25,516	44.5%	1,262,041,558	56.8%
Deutsche Post	102,557	52.2%	18,433	45.6%	581,767,692	33.8%	93,961	47.8%	21,996	54.4%	1,141,426,973	66.2%
Deutsche Postbank	59,799	51.6%	10,870	53.6%	168,314,037	41.6%	56,156	48.4%	9,412	46.4%	236,143,832	58.4%
Deutsche Telekom	113,233	51.6%	19,752	42.9%	1,012,429,825	33.3%	106,378	48.4%	26,312	57.1%	2,032,458,637	66.7%
E.ON	265,464	56.1%	40,173	62.4%	1,529,680,829	56.0%	207,421	43.9%	24,173	37.6%	1,200,954,629	44.0%
Fresenius Med. Care	107,384	69.0%	12,486	58.6%	158,454,475	53.1%	48,137	31.0%	8,835	41.4%	140,202,386	46.9%
Henkel	76,442	52.0%	12,235	46.5%	185,661,502	35.9%	70,543	48.0%	14,099	53.5%	332,024,227	64.1%
Hypo Real Estate	123,036	50.4%	19,458	51.5%	361,043,311	41.5%	120,956	49.6%	18,343	48.5%	508,391,772	58.5%
Infineon	98,330	60.0%	16,354	50.5%	469,101,313	40.5%	65,612	40.0%	16,011	49.5%	687,931,908	59.5%
Linde	134,642	62.6%	18,179	65.0%	333,153,037	55.6%	80,345	37.4%	9,800	35.0%	265,873,348	44.4%
Lufthansa	135,855	65.7%	20,766	61.6%	384,794,459	51.5%	71,015	34.3%	12,927	38.4%	361,693,494	48.5%
MAN	172,761	51.2%	25,917	52.6%	619,494,708	38.1%	164,805	48.8%	23,325	47.4%	1,005,383,018	61.9%
Merck	78,830	66.8%	15,212	57.8%	307,386,567	43.9%	39,156	33.2%	11,096	42.2%	392,933,902	56.1%
Metro	77,147	51.7%	11,448	54.0%	221,789,717	40.6%	72,191	48.3%	9,755	46.0%	324,935,561	59.4%
Münchner Rück	212,972	48.1%	31,270	62.4%	881,141,537	50.9%	230,222	51.9%	18874	37.6%	848,692,136	49.1%
RWE	155,455	41.5%	30,675	58.6%	997,175,684	48.5%	218,999	58.5%	21,642	41.4%	1,060,109,271	51.5%
SAP	243,279	51.4%	57,515	48.3%	2,049,684,431	37.9%	230,183	48.6%	61,585	51.7%	3,353,838,483	62.1%
Siemens	278,179	55.4%	43,853	59.0%	1,786,939,922	50.4%	224,035	44.6%	30,525	41.0%	1,756,968,604	49.6%
ThyssenKrupp	158,403	64.2%	25,090	62.3%	442,257,844	46.9%	88,513	35.8%	15,192	37.7%	500,350,048	53.1%
TUI	65,474	52.0%	10,934	50.2%	180,619,398	36.4%	60,343	48.0%	10834	49.8%	315,919,291	63.6%
Volkswagen	229,196	35.8%	54,846	53.1%	1,779,973,952	36.5%	411,168	64.2%	48,410	46.9%	3,091,171,437	63.5%
Total	4,624,052	52.3%	814,068	54.7%	24,389,078,240	43.0%	4,216,928	47.7%	674,758	45.3%	32,365,680,126	57.0%

Table 1. ATP and Non-ATP activity during continuous trading

In the following a deeper analysis distinguishing aggressor and non-aggressor orders is performed: If aggressive executions are considered (Table 2), in total 56% of all aggressive executions are triggered by an ATP order as the aggressor. *Linde* has the highest share of ATP executions as in 68.4% an ATP trader was the aggressor. Further *E.ON* catches attention, as about two out of three executions were triggered by ATP orders, which sum up to 63.6% of the total value traded. For *Deutsche Post* only 30.5% of the executed value has been triggered by aggressive ATP orders. Please note that for the execution perspective of aggressors, the traded value is only single-counted.

Instrument	ATP Aggressor				Non-ATP Aggressor			
	#Exec.	Share	Value (€)	Share	#Exec.	Share	Value (€)	Share
Adidas	5,871	51.8%	147,727,670	40.1%	5,463	48.2%	220,465,985	59.9%
Allianz	17,939	58.3%	815,830,769	54.6%	12,850	41.7%	677,666,105	45.4%
BASF	12,284	63.6%	484,743,607	54.8%	7,020	36.4%	399,148,772	45.2%
Bayer	14,661	59.1%	527,693,979	45.5%	10,158	40.9%	631,532,720	54.5%
BMW	7,759	54.4%	238,952,064	46.7%	6,509	45.6%	272,935,985	53.3%
Commerzbank	10,674	47.3%	378,816,418	33.4%	11,890	52.7%	754,370,222	66.6%
Continental	7,428	50.9%	203,448,578	39.6%	7,164	49.1%	310,383,456	60.4%
Daimler	22,544	58.5%	1,175,580,710	50.1%	15,974	41.5%	1,172,049,546	49.9%
Deutsche Bank	17,440	54.1%	928,326,908	49.2%	14,777	45.9%	957,613,348	50.8%
Deutsche Börse	13,079	55.1%	469,338,882	42.2%	10,663	44.9%	643,135,171	57.8%
Deutsche Post	6,329	45.1%	262,851,251	30.5%	7,707	54.9%	599,295,719	69.5%
Deutsche Postbank	4,343	54.5%	91,187,404	44.7%	3,622	45.5%	112,663,825	55.3%
Deutsche Telekom	8,217	47.7%	520,195,714	34.1%	9,007	52.3%	1,005,149,069	65.9%
E.ON	17,075	66.0%	868,643,705	63.6%	8,792	34.0%	498,175,815	36.4%
Fresenius Med. Care	4,930	57.1%	79,234,895	52.7%	3,704	42.9%	71,045,150	47.3%
Henkel	4,603	44.7%	95,672,277	36.8%	5,688	55.3%	164,456,873	63.2%
Hypo Real Estate	7,587	50.5%	172,726,254	39.6%	7,438	49.5%	263,415,025	60.4%
Infineon	6,232	53.1%	230,418,056	39.8%	5,512	46.9%	349,128,733	60.2%
Linde	7,916	68.4%	179,499,154	59.8%	3,651	31.6%	120,725,624	40.2%
Lufthansa	8,285	65.6%	207,102,360	55.3%	4,337	34.4%	167,104,966	44.7%
MAN	10,385	50.6%	321,400,018	39.4%	10,159	49.4%	494,482,872	60.6%
Merck	6,132	58.0%	153,803,815	43.8%	4,448	42.0%	197,056,651	56.2%
Metro	4,890	57.5%	122,000,709	44.6%	3,613	42.5%	151,714,068	55.4%
Münchner Rück	13,263	64.5%	496,915,991	57.4%	7,313	35.5%	369,170,149	42.6%
RWE	13,280	63.4%	567,663,548	55.1%	7,671	36.6%	462,435,466	44.9%
SAP	23,196	50.3%	1,116,400,830	41.2%	22,879	49.7%	1,593,677,930	58.8%
Siemens	18,266	59.3%	1,002,700,087	56.4%	12,516	40.7%	773,706,990	43.6%
ThyssenKrupp	9,446	59.7%	227,957,798	48.1%	6,368	40.3%	246,201,736	51.9%
TUI	4,101	48.9%	92,710,494	37.2%	4,285	51.1%	156,649,695	62.8%
Volkswagen	24,282	55.1%	934,060,563	38.2%	19,787	44.9%	1,508,144,901	61.8%
Total	332,437	56.0%	13,113,604,506	46.1%	260,965	44.0%	15,343,702,566	53.9%

Table 2. Number of executions and executed value for ATP- and Non-ATP aggressors in continuous trading

Table 2 further discloses that though across all securities 56.0% of all executions are triggered by aggressive ATP orders, they represent only 46.1% of the totally traded value. The average value per executed order for ATP aggressor executions is 39,447 € and the average value per executed order for Non-ATP aggressor executions is 58,796 €. There are two possible explanations:

1) *ATP users have more partial executions*
A possible explanation for the fact that more executions result in less executed volume would be that aggressive Algorithmic Trading orders have more partial executions boosting their total

number of executions. If the algorithms submit orders that hit orders at several price levels, this would result in several executions and the value per execution would be lowered.

However, this argument does not hold true. This can be checked by measuring the number of different timestamps for the respective executions as multiple executions at the same timestamp represent partial executions. As there are 332,437 ATP aggressor executions at only 278,374 different timestamps, 19.4% of the aggressor orders seem to cause executions at several price levels. But for the Non-ATP aggressors there are 260,965 executions at 209,919 distinct timestamps indicating that 24.3% of Non-ATP aggressor orders cause more than one execution.

2) *Algorithms submit more but smaller orders*
Assuming that the algorithms can monitor changes in the order book and react in real-time and given that they still get what they saw when their order is arriving at the market, algorithms look for advantageous limits in the order book and snap at the chance and execute the best bid or offer. As the top of the book most often is thin – as the most volume is just behind the best bid and offer – this results in more but smaller executions. Furthermore the smaller executions lead to less market impact than larger executions that would potentially hit more than one price level.

For non-aggressor orders, Table 3 presents evidence that ATP non-aggressor orders (i.e. limit orders that are not immediately executable) are also smaller than their Non-ATP counterparts as it depicts the average order volumes and average order values (order volume times order limit). The surplus of Non-ATP orders' average value over ATP orders' average value is 143.5% for all securities. The values for the individual instruments range from 40.6% (*Linde*) to 455.7% (*Volkswagen*). Please note that iceberg orders and their peaks have not been considered for the calculation of the averages.

	ATP Non-Aggressor Orders				Non-ATP Non-Aggressor Orders				Avg. Value Surplus
	#	Share	Avg. Volume	Avg. Value (€)	#	Share	Avg. Volume	Avg. Value (€)	
Adidas	37,007	53.9%	566	25,011	31,711	46.1%	1,104	48,854	95.3%
Allianz	119,618	51.2%	291	47,484	114,208	48.8%	566	92,271	94.3%
BASF	68,921	59.3%	468	44,842	47,308	40.7%	754	72,447	61.6%
Bayer	65,683	59.4%	643	36,201	44,877	40.6%	1,120	62,886	73.7%
BMW	41,761	51.5%	568	26,929	39,335	48.5%	1,087	51,566	91.5%
Commerzbank	47,947	48.1%	934	28,649	51,665	51.9%	1,532	47,062	64.3%
Continental	46,749	62.9%	241	23,903	27,564	37.1%	620	61,458	157.1%
Daimler	48,249	48.1%	321	34,043	52,152	51.9%	746	79,158	132.5%
Deutsche Bank	108,964	54.1%	488	45,729	92,584	45.9%	791	74,311	62.5%
Deutsche Börse	97,228	48.6%	803	59,373	102,636	51.4%	1,221	90,798	52.9%
Deutsche Post	23,812	60.2%	379	20,553	15,714	39.8%	803	45,553	121.6%
Deutsche Postbank	41,370	56.3%	1,392	29,818	32,094	43.7%	2,271	50,189	68.3%
Deutsche Telekom	43,692	54.8%	3,652	50,061	36,075	45.2%	6,247	85,648	71.1%
E.ON	108,008	54.7%	424	54,359	89,328	45.3%	733	93,872	72.7%
Fresenius Med. Care	45,735	71.1%	527	19,137	18,566	28.9%	1,208	43,908	129.4%
Henkel	31,483	55.5%	431	15,296	25,269	44.5%	793	28,052	83.4%
Hypo Real Estate	50,448	56.7%	450	19,920	38,451	43.3%	928	40,962	105.6%
Infineon	40,143	66.5%	2,523	27,996	20,232	33.5%	3,681	40,836	45.9%
Linde	55,312	68.2%	1,186	25,134	25,801	31.8%	1,665	35,329	40.6%
Lufthansa	56,682	62.7%	302	27,133	33,679	37.3%	743	66,842	146.3%
MAN	71,643	52.0%	240	28,685	66,079	48.0%	778	92,974	224.1%
Merck	31,709	51.6%	500	31,063	29,797	48.4%	1,015	63,028	102.9%
Metro	30,851	72.5%	293	26,189	11,719	27.5%	444	39,497	50.8%
Münchner Rück	87,952	46.2%	242	33,263	102,499	53.8%	630	86,497	160.0%
RWE	59,150	38.3%	473	42,123	95,325	61.7%	789	70,133	66.5%
SAP	88,309	53.9%	943	37,333	75,524	46.1%	1,452	57,548	54.1%

Siemens	112,847	55.3%	544	53,282	91,121	44.7%	869	85,074	59.7%
ThyssenKrupp	64,648	66.3%	519	23,253	32,912	33.7%	900	40,428	73.9%
TUI	26,850	56.3%	924	18,627	20,839	43.7%	1,931	38,896	108.8%
Volkswagen	80,832	31.7%	265	47,027	174,075	68.3%	1,480	261,346	455.7%
Total	1,833,603	52.8%	648	37,447	1,639,139	47.2%	1,160	91,192	143.5%

Table 3. Average volumes and values of submitted non-aggressor orders in continuous trading

Concerning research question 1, the data reveals that Algorithmic Trading is a relevant part of technical events, actual executions as well as order submissions. Algorithms tend to use smaller order volumes both for aggressive as well as for non-aggressive orders than (human) Non-ATP counterparts.

Research question 2: *Does Algorithmic Trading activity, i.e. do actual orders submitted by Algorithmic Trading engines, reflect their technical ability to monitor and exploit real-time market movements and market information when algorithms **execute orders aggressively**?*

Research question 2 relates to the (aggressive) execution behavior of algorithms and is addressed in two dimensions: 2a) concerning the usage of order types by algorithms versus human traders and 2b) concerning the submitted limits in case of aggressive limit orders by algorithms versus human traders.

2a) If ATP traders would be more aggressive one might assume that they will utilize market orders to a larger extent than Non-ATP traders. As Table 4 points out, this is not the case, as although there is a similar number of ATP and Non-ATP orders involved in continuous trading, only 6.2% of the market orders have been submitted by ATP users. A straight forward Chi-Square Test shows that the null-hypothesis of equal likelihood for ATP and Non-ATP participants to either utilize limited orders (limit and iceberg orders) or market orders can be rejected at a p-value of 0.01, which reveals a highly significant difference. The vast majority of ATP submitted orders are limit orders as an aggressive strategy can be implemented with limit orders and a smart setting of the limits as well. Such a strategy is eased by speed and low latency to monitor market movements in real-time and to react with minimum delay – a prerequisite that can be matched by machines.

Ordertype	ATP		Non-ATP	
	Occurrences	Share	Occurrences	Share
Limit	2,145,968	53.9%	1,832,175	46.1%
Market	3,042	6.2%	46,352	93.8%
Iceberg	4,739	8.0%	54,137	92.0%
Market-To-Limit	0	0.0%	587	100.0%
Total	2,153,749	52.7%	1,933,251	47.3%

Table 4. Utilization of order types by ATP and Non-ATP traders in continuous trading

2b) In the following the focus is laid on how algorithms set order limits when implementing an aggressive strategy. Based on the succession of order events in the dataset, the state of the order book has been reconstructed event-by-event for each single point of time in the observation period. The determined executions based on this order book reconstruction have been validated against actual executions reported in the dataset. The reconstruction of the order book enables to investigate order submissions relative to the best bid and offer limits (the spread) prevailing at the time of submission. Although ATP and Non-ATP exhibit a similar share of aggressive orders (ATP: 14.6%, Non-ATP: 11.2%; see research question 1), the applied limits relative to current best bids and offers differ clearly (Table 5). 67.8% of all order submissions that exactly match the best bid or offer are ATP orders. Nearly two thirds of the other aggressive submissions are Non-ATP orders. For ATP orders, even 85.1% of the aggressive orders are limited exactly to the best available limit in the order book. A Chi-Square Test shows that the null-hypothesis of equal likelihood of ATP and Non-ATP orders to submit exact limit matches can be rejected at a p-value of 0.01, i.e. reveals a highly significant difference.

	ATP		Non-ATP	
	Occurrences	Share	Occurrences	Share
Exact Limit Matches	270,132	67.8%	128,229	32.2%
Other Matches	47,219	34.8%	88,531	65.2%
Total Matches	317,351	59.4%	216,760	40.6%

Table 5. Distribution of exact limit matches

Further, 17.7% of aggressive ATP orders are also exactly matching the volume available at the best limit (Non-ATP: 7.9%). Out of all submissions that exactly match the opposite side's limit and volume 76.7% are ATP orders. For high-liquid securities, such as *Siemens* or *E.ON*, this proportion is even higher (92.1% respectively 91.9%). Referring to research question 2, these results indicate that ATP orders' limits and volumes are based on a real-time monitoring of the market and are set based on latest market movements.

Research question 3: *Does Algorithmic Trading activity, i.e. do actual orders submitted by Algorithmic Trading engines, reflect their technical ability to monitor and exploit real-time market movements and market information when algorithms* ***position non-aggressive orders*** *in the order book?*

Research question 3 relates to the (non-aggressive) submission behavior and can be addressed in two dimensions: 3a) concerning the positioning of non-aggressive orders by algorithms versus human traders relative to the current best bids or best offers and 3b) concerning the adaptation of limits by algorithms versus human traders in case of changing best bids or best offers.

3a) Table 6 points out the different positioning of non-aggressive ATP- and Non-ATP orders. Of the non-aggressive orders that improve the spread, 75.9% are ATP orders, while of the orders that do not affect the spread 62.5% are Non-ATP. A Chi-Square Test (null-hypothesis: equal likelihood of ATP and Non-ATP orders to improve the spread) can be rejected at a p-value of 0.01, i.e. again reveals a highly significant difference among ATP and Non-ATP orders. The different order positioning behavior can also be seen from the weighted-average absolute variation in cents by which orders narrow the spread. ATP orders improve the best limit on average by 1.38 cents while Non-ATP orders improve it by 1.95 cents, i.e. algorithms are able to position orders at the top of the book with a lower concession in terms of price improvement.

	ATP		Non-ATP	
	Occurrences	Share	Occurrences	Share
Spread Improvement	1.007.781	75,9%	320.496	24,1%
No Spread Improvement	830.350	37,5%	1.385.458	62,5%
Total	1.838.131		1.705.954	

Table 6. Distribution of spread improvements

3b) As shown above, ATP market participants limit the majority of their non-aggressive order in a way to be at the spread by either adding volume to the existing spread limit or setting a better limit. As these orders are positioned at the top of the book, i.e. they have a high likelihood of execution, it is of interest to investigate their further lifetime. The following table 7 depicts what happens to orders that are part of the spread when their lifetime ends. The absolute figures reveal that there are by far more ATP orders that end their lifetime being at the spread. As for table 7 the distribution of the termination reasons is in the focus, the percentages are calculated in relation all termination reasons at the spread for each ATP and Non-ATP. About two thirds of Non-ATP orders end their lifetime at the spread by getting executed, while about one third gets deleted. For ATP orders these ratios are nearly vice versa. 63.2% of the ATP orders that end their lifetime being part of the spread are deleted. Again, the Chi-

Square Test (null-hypothesis: equal likelihood of ATP and Non-ATP orders to be terminated by execution; p-value of 0.01) reveals a highly significant difference between ATP and Non-ATP orders.

The third and sixth column (table 7) lists the average time in milliseconds that the orders were continuously part of the spread before termination. The average survival times for orders terminated by execution are similar. This meets the expectation, as for executions the survival time is determined by other (aggressive) orders and therefore can not be influenced by the order positioned at the spread. However, for deleted Non-ATP orders the survival time is nearly twice the one for deleted ATP orders. 63.2% of ATP orders are deleted on average 6.529 seconds after becoming part of the spread. At a first glance it seems as if ATP users initially submit orders at the spread and then get cold feet and delete their orders to avoid execution. But what seems to be a deletion is actually a modification. As within the Xetra market model only a reduction of order volume does not affect price-time priority while all other modifications are mapped to a deletion event and a subsequent submission event for the 'new' modified order. For 26.9% of the ATP orders deleted at the spread there is an ATP submission event of a new order in the same instrument at exactly the same timestamp, with the same direction (buy or sell) and exactly the same volume (Non-ATP: 23.2%). If the restrictions are relaxed (up to 1 second delay, +/-5% volume), there is a corresponding submission event for 40.2% of the ATP deletions (Non-ATP: 33.4%) out of which 115,331 again improve the spread (Non-ATP: 16,822). This indicates that ATP traders want their orders to be at the top of the book. Therefore, they emulate pegging orders at their front end (an order type where the limit tracks the best bid or offer and moves with the market) as this order type – contrary to other markets – is not provided by the Xetra back-end.

	ATP			Non-ATP		
	Events	Distribution	Avg. Survival time (ms)	Events	Distribution	Avg. Survival time (ms)
Execution	293,142	36.8%	17,927	184,009	64.9%	20,072
Deletion	503,650	63.2%	6,519	99,674	35.1%	11,731
Total	796,792	100.0%	10,716	283,410	100.0%	17,141

Table 7. Survival time and termination reason for orders at the spread

To sum up the data analyzed concerning research question 3, the results indicate that ATP traders are more aware of the current spread, as they more often reflect the current best bid or ask when limiting their orders, and that their orders about three times more often narrow the current spread. Furthermore, they control their orders relative to the current market situation and delete and reinsert their orders based on changes in the current spread more extensively than Non-ATP traders.

5 CONCLUSION

The detailed implementations of Algorithmic Trading systems are not published as these constitute important intellectual property rights of investment firms and are a key component of their business models both for proprietary trading and when providing algorithms to customers (regularly as a black box). Therefore, only little is known about how Algorithmic Trading engines schedule their trading and adapt to current market movements. Based on a unique dataset from a market operator that includes a tag enabling to distinguish Algorithmic Trading engines and human traders, the results show that the submission and deletion behavior of those systems (statistically) significantly differs from other market participants'. Evidence has been presented that Algorithmic Trading systems submit orders that are noticeably smaller. Additionally they show the ability to monitor their orders and modify them to be at the top of the book. Applying Chi-Square Tests shows that Algorithmic Trading behavior is fundamentally different to human trading concerning the use of order types, the positioning of limits in case of executions and submissions as well as their modification/deletion behavior. These results let us conclude that Algorithmic Trading systems capitalize on their advantageous ability to process high-speed data feeds and react instantaneously to market movements by submitting corresponding orders or modifying existing ones.

Future research based on the dataset will both investigate order submission strategies in auctions and the contribution of Algorithmic Trading engines to overall market liquidity. This contributes not only to the understanding of the algorithmic implementations but also to market design and market surveillance issues. Furthermore, the understanding of algorithmic behavior enables to identify potential functional or technical bottlenecks especially in peak load periods.

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