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Algorithmic Trading Patterns in Xetra Orders

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ABSTRACT *Computerized trading controlled by algorithms – "Algorithmic Trading" – has become a fashionable term in investment banking. We investigate a set of Xetra order data to find traces of algorithmic trading by studying the lifetimes of cancelled orders. Even though it is widely agreed that an algorithm must randomize its order activities to avoid exploitation by other traders, we still find systematic patterns in the submission and cancellation of certain Xetra orders, indicating the activity of algorithmic trading. The trading patterns observed might be interpreted as fishing for profitable roundtrips.*

KEY WORDS: Market microstructure, algorithmic trading, cancellations, order lifetime, Xetra

1. Introduction

Algorithmic trading has become a standard technique in most investment firms. Algorithms are capable of submitting ever larger streams of orders to the electronic order book at increasing speeds. A recent statement by Deutsche Börse AG mentioned that 37% of trades currently originate from algorithmic trading (cf. Deutsche Börse AG (2006)), while Gomber and Groth (2006, p. 50) estimate up to 40% of algorithmic trade volume. It seems quite obvious that an algorithm should "*randomize how it sends orders in the market, how it prices orders, and the way it cancels and replaces those orders. Otherwise, someone could see that order coming and prepare to make money on it*" (quote from Hiresh Mittal of ITG in Mehta (2005), cited in: Schwartz *et al.* (2006, p. 301)).

In response to the needs of algorithmic trading, continuing improvements in the network infrastructure of Deutsche Börse AG have caused roundtrip[1] times to decline to ever lower levels. Recent roundtrip times have fallen to the level of 20 milliseconds and are expected to reach a level of 10 milliseconds by April 2007 (cf. Deutsche Börse AG (2007)). At the same time, leading event stream processing systems have to cope with the challenge of reaching latencies in the range of milliseconds (cf. Stonebraker *et al.* (2006), Bates and Palmer (2006), Aleri Labs (2006)). Event stream processing tracks, as the term indicates, individual events (see Luckham (2002)). Investigating algorithmic trading therefore also benefits from investigating individual events, e.g., the insertion, cancellation or completion of single orders.

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Short roundtrip times in combination with the low decision-making latency of algorithms offer ideal trading conditions for fully automated trading systems, enabling them to respond to new conditions in the sub-second range. As these response times are key to the analysis of algorithmic trades, we note the high precision of the time stamps in our dataset. These time stamps of order events are recorded with a precision of one hundredth of a second. Thus, using this set of individual orders, we are able to carry out detailed lifetime studies and search for algorithms using lifetime deviations in the sub-second range.

In this paper, we primarily focus on the time dimension for identifying traces of algorithmic trades. With respect to time analysis there is a large body of literature on so-called *financial duration processes* that allow us to define basically any event of interest and the corresponding duration sequence; the applications so far mostly focus on aggregates and not on individual orders. Graming and Maurer (2000) adapt the autoregressive conditional duration (ACD) model proposed by Engle and Russell (1998) to analyse (NYSE) price durations. Engle and Dufour (2000) investigate NYSE price durations by applying a vector autoregressive model, originally proposed by Hasbrouck (1991). Engle and Lunde (2003) generalize the ACD model to analyse both transactions and quotes in a Trade and Quote (TAQ) database from the NYSE. Hall and Hautsch (2006) model the most aggressive order submissions using an autoregressive conditional intensity model, which was originally introduced by Russel (1999). In these models, the financial durations are commonly generated by data “thinning”, i.e., the selection of particular points in the all-embracing trading (point) process (see, e.g., Bauwens and Giot (2001, p. 45)). Trade duration is defined as the time between two transactions and price duration is defined as the equivalent of a first passage time of the price process (see, for instance, Hautsch (2004, p. 4)). The analysis of durations is restricted if quotes and trades are in different databases such as in the NYSE’s TAQ database. Another issue is in identifying the buyer and seller initiated trades (see Engle and Dufour (2000) who used Trade, Order, Report, Quote (TORQ) data). Lee and Ready (1991) proposed the “five seconds rule” and the “mid-quote rule”, respectively, for approximately solving these issues. For a treatment of problems in the data preparation process for the application of duration models, see Hautsch (2004).

In our study, we calculate and analyse the lifetime of an order by tracking the points of the trading process (events) *within* an order. In our dataset from the Xetra system of Deutsche Börse AG, orders are identified by a unique identifier. Therefore, for each order, the full history of events such as order insertion, deletion, execution, partial execution or modification can be followed. For each event the full details of the order, except identification of the trader or the exchange member involved, are given. The detailedness of the dataset allows the identification of each order involved in a matching of orders as well as the identification of buyer and seller initiated trades. We are not forced to rely on the approximation rules mentioned above for TAQ/TORQ like databases.

For investigating the algorithmic trading features in the Xetra order book, we concentrate our analysis on the lifetimes of the so-called no-fill-deletion orders, i.e., orders that are inserted and subsequently cancelled. We find previously undiscovered specific patterns in cancelled orders’ lifetimes from the reconstructed order book data of Deutsche Börse’s Xetra system. We investigate these patterns in cancelled orders’ lifetimes on an order-by-order basis, i.e., by analysing the existing orders and the corresponding detailed order event entries in the order book. Our investigation leads us to evidence of activities of automatons placing orders on the buy and sell side. We define the criteria for filtering sequences of orders, which we term constant-initial-cushion (CIC) orders, providing a case study of algorithmic trading in the Xetra Order book. The strategy behind these algorithmic orders seems to be consistent with a result from Handa and Schwartz (1996). In that paper, the authors investigated the use of limit orders versus market orders but also tested a pure limit orders trategy that consisted of a network of bid and ask orders placed around the current price.

Several other studies investigating order lifetimes and cancellations have been conducted. A study focusing on the lifetimes of limit orders executed was carried out by Lo *et al.* (2002). The authors use survival analysis and a data sample of orders from an institutional investor to develop an econometric model of limit-order execution lifetimes. They report detailed survival functions for time-to-completion, time-to-first-fill for the range from 0 to 60 minutes. Hasbrouck and Saar (2005) investigate Island ECN orders and mention a large proportion of "fleeting orders", i.e., very short-lived orders with lifetimes below two seconds terminated by cancellation inside the spread. They attribute them to the search for "hidden liquidity" made possible by the microstructure of the Island ECN. Boehmer *et al.* (2005) analyse the special open limit order book and find decreasing order sizes and faster cancellation, and thus shorter lifetime of cancelled orders than before the introduction of the NYSE Open Book service. This NYSE Open Book service provides information about limit orders every 10 seconds and, as the authors note, may be too slow for certain types of automated trading strategies that investors may want to implement off the exchange floor.

The remainder of the paper is organized as follows: Section 2 describes the market model of Deutsche Börse's Xetra system as well as the specifics of our dataset. Section 3 examines the lifetimes of cancelled Xetra orders, illustrates patterns resulting from algorithmic trading activity and gives a possible explanation for the strategy of the algorithmic trades. Section 4 summarizes and concludes. In keeping with an increasingly common practice, only the main results are presented in the paper. More detailed results are available on request from the corresponding author.

2. The Frankfurt Stock Exchange and the Dataset

2.1 The Database

As the basis for our research, we use the complete record of the order book events from the Xetra system of Deutsche Börse AG. Two different time periods, each of which contains six trading days were used. The first database contains the record of all order book changes occuring in the time from 8 to 15 December 2004. The second data base contains all changes in the time from 5 to 12 January 2005.

The first database consists of 4 794 741 entries and the second one of 5 014 200 entries records changes in the electronic order book of the Xetra system. Note that the database entries themselves do not explicitly contain information such as best bid and best ask or current reference price. Instead, a database entry is generated whenever an order is entered into the system, partially executed, fully executed, cancelled, modified, automatically entered or automatically cancelled. Every such order event is time-stamped at the moment it is processed by the Xetra order book software. The time-stamps in our dataset feature a precision of One hundredth of a second while the Xetra system itself operates with a precision level of One thousandth of a second. Thus, the timing accuracy in our dataset almost matches the accuracy of the real Xetra engine. The matching algorithm of Xetra relies on these time-stamps to execute trades according to the price-time priority rules given in the Xetra market model (cf. Deutsche Börse AG (2004)).

Information such as best bid, best ask and current reference price can be reconstructed from the order events. In order to find the best bid, best ask or current order book depth for any given time t, it is necessary to find the subset of orders valid at time t, according to the Xetra market model and the order restrictions given as parameters to each order. These orders are then sorted in a table according to price priority such that the current available volume for buying and selling at any given limit can be computed. A similar procedure can be used to find the current reference price. By sorting order events according to their time stamps and then finding the most recent order execution price before t, the reference price can be reconstructed from the order data. The individual events will be described in more detail in Section 2.4.

In order to avoid data-snooping effects, the initial research for this paper, including definition of the filtering criteria for CIC orders, was done using the database containing all order book events from 8 to 15 December 2004. The tables and figures in this paper were then generated *out of sample* using the second database that describes all changes to the order book occurring in the six trading days from 5 to 12 January 2005.

2.2 The Frankfurt Stock Exchange

Deutsche Börse AG runs the Frankfurt Stock Exchange (FWB). It is by far the most important among the eight German stock exchanges and offers floor trading as well as fully-electronic trading on Xetra. Approximately 97% of all trading involving the DAX-30 stocks of our sample are done via Xetra (cf. Deutsche Börse AG (2005)). While many of the DAX-30 stocks are also listed on other exchanges, the vast majority of trading for these stocks happens on the Xetra system.

Xetra offers remote access: some 350 brokers and broker firms from 18 countries participate in the trading. Xetra trading is organized as a hybrid system combining auctions and continuous trading. For the DAX-30 stocks in our sample, a pre-trading phase from 7:30 to 8:50 hours offers the opportunity to enter orders into Xetra. The functioning of order driven markets is thoroughly explained by Schwartz *et al.*, (2006, pp. 73–75). Following the pre-trade phase, an opening auction with a randomly timed end around 9:00 hours provides the first executions of each trading day (cf. Deutsche Börse AG (2003)). After the opening auction, the system switches to continuous trading until the intraday auction at 13:00 hours, again with a randomly timed ending. This intraday auction is again followed by continuous trading until the closing auction at 17:30 hours, again featuring a randomly timed ending. A volatility break and an additional auction occur whenever the price leaves a pre-fixed price band.[2] Continuous trading follows the price-time priority rule (cf. Deutsche Börse AG (2004) for the details of the matching algorithm).

2.3 Order Types

The Xetra system allows four different types of orders:

Limit order. Limit Orders comprise the lion's share of the Xetra order book. The Limit Order is characterized by a limit on the price that the submitter is willing to accept. Those orders with a lower (higher) price limit for an ask (bid) order get higher priority for being executed.

Market order. Market Orders do not feature any restriction on the price the submitter is willing to accept. Therefore, they are executed immediately, possibly generating several trades, sometimes even with different transaction prices if the order size is larger than the best order on the other side. This property is commonly known as "walking up the book".

Market-to-limit order. Market-to-Limit orders are similar to market orders matching the best order on the other side, if completely filled. If the Market-to-Limit order is not completely filled at the best limit on the other side, the remaining part will enter the order book as a limit order with exactly that limit.

Iceberg orders. Iceberg orders split up the entire volume into visible parts of smaller size and only display one such part at a time as a limit order. As soon as the disclosed limit order is completely filled, a new limit order of the same size will be entered into the order book automatically by the system. This process is repeated until the whole volume of the iceberg order is matched or the order is cancelled.

For limit and market orders, additional flags and restrictions governing the execution handling can be supplied. The most important restrictions are the following three flags:

Fill-or-kill (F). This restriction will cause the system to check if the order can be completely matched immediately. If this is possible, the order will be executed. Otherwise it will be deleted immediately.

Immediate-or-Cancel (I). This restriction will cause the system to execute all matches that are possible at the order's arrival time point. Any remaining part that cannot be matched immediately will be deleted immediately.

Triggered-Stop-Order (S). This order is entered into the order book automatically as soon as the predefined stopping conditions are met.

2.4 Order Event Codes and Order Event Sequences

In the following, we use a database that contains all changes to the order book occurring on the six trading days in the time from 5 to 12 January 2005, as described in Section 2.1. It consists of 5 014 200 database entries recording changes in the electronic order book of the Xetra system. The database entries consist of different event types. Each event type's code and frequency are listed in Table 1.

Table 1. Frequency of different events in the database

Event type	Event code	Absolute frequency	% Entry[b]	% Termination[c]
Order entry[a]	1	2 284 628	99.98	
Order modification	2	36 165		
Order cancellation	3	1 626 896		70.15
Order filled completely	4	675 232		29.12
Order partially filled	5	373 760		
Order deleted automatically	6	16 597		0.72
Technical Entry	101	461	0.02	
Technical Cancellation	103	461		0.02

Frequency of different events in the database along with their event code found in the time 5–12 January 2005. A total of 5 014 200 database entries were examined. Absolute count data are given in the middle column, while the two rightmost columns list the percentage of orders started/ended via each respective event code.

[a]Due to the restriction of the dataset to a certain observation period, there were some orders where the order entry was not observable in the dataset. Similarly, there were orders without a suitable end of code 3, 4, 103 or 6. This is the reason why the sum of order entries (code 1 and code 101 adds up to $2\,284\,628 + 461 = 2\,285\,089$) does not match the sum of order terminations (code 3, 4, 6 and 103 adds up to $1\,626\,896 + 675\,232 + 16\,597 + 461 = 2\,319\,186$).

[b]Percentage of orders, that are entered via a 1 resp. 101 code. Hundred percent comprises all order entry events in the database.

[c]Percentage of orders terminated via a 3, 4, 6 resp. 103 event. Hundred percent comprises all order terminating events in the database.

Table 2. Example: 1–5–5–3 order

Modificationtimestamp	Event code	Buysell	Limit	Price	Size
5 January 2005 09:51:27.87	1	S	35.00	0.00	20 000
5 January 2005 13:11:55.05	5	S	35.00	35.00	2485
5 January 2005 16:27:13.58	5	S	35.00	35.00	377
5 January 2005 16:27:16.11	3	S	35.00	0.00	17 138

The order is inserted with a volume of 20 000 at time 09:51:27.87. Partial execution with a size of 2485 reduces the available volume to $20\,000 - 2485 = 17\,515$ at time 13:11:55.05 and then another partial execution of 377 units leads to $20\,000 - 2485 - 377 = 17\,138$ remaining units from 16:27:13.58. At 16:27:16.11 the remaining volume of 17 138 units is cancelled altogether. Further data fields omitted in this table include the order expiry date, auction trade flag, order type, order restriction, trade restriction, order entry timestamp, order number and ISIN code.

Every new order submission generates an event with event code 1. Cancellation generates an event with code 3. Full execution generates an event with code 4. Therefore, orders that are entered into the system and then deleted again without any executions generate event code sequences characterized by 1–3. These orders are often termed *no-fill deletion* orders. Orders that are entered into the system and then filled in a single transaction generate event code sequence 1–4. These orders are usually termed *one-fill completed* orders. Many orders also feature events of partial executions each generating event code 5. This leads to sequences of type 1–5–5–· · ·–5–3. The last event code 3 indicates that the remaining part of the order has been cancelled. In the sequence 1–5–5–· · ·–5–4 the last event code indicates that the remaining part of the order has been executed entirely. These orders also are of interest, but do not get a special name here. An example illustrating a 1–5–5–3 order is given in Table 2.

The number of order modifications characterized by a code 2 event is rather small. It does not even add up to a single percentage point. This fact indicates that the primary method of changing existing orders is obviously to cancel the old order and re-submit another one (cf. Deutsche Börse AG (2004), p. 11).

The vast majority of orders belong to the 1–3, 1–4, 1–5–4 and 1–5–3 type. Table 3 shows the frequencies of the most common sequence codes in conjunction with different order types.

Table 4 exhibits the frequency of each order type in combination with the order restrictions explained in Section 2.3

Tables 3 and 4 indicate that limit orders play the most important role in Xetra in terms of number of orders entered into the system as well as concerning traded volumes. The dominance of limit orders is greater when comparing the number of orders. This is due to the fact that the typical volume of limit orders is lower than that of iceberg orders or market orders. Iceberg orders are an instrument typically used to trade larger volumes with a single order. In the money volume part of the table, the iceberg orders do show up considerably stronger than in the pure order count part. In this paper we investigate limit orders only. For the investigation of iceberg orders see Mönch (2005).

2.5 More Actively and Less Actively Traded Stocks in the Sample

We use the actual trades' money volume as a proxy for liquidity of each stock in the DAX-30. The results and ranking according to this measure are given in Table 5.

Table 3. Event code sequences for order types and order restrictions in the Xetra order book from 5 to 12 January 2005

Ordertype/Sequence combinations[a]	Absolute freq.	% of ordertype	% of all entries
L with seq. 1–3.	1 481 005	67.29	64.82
L with seq. 1–4.	471 348	21.42	20.63
L with seq. 1–5–4.	80 175	3.64	3.51
L with seq. 1–5–3.	41 508	1.89	1.82
(Other)	126 832	5.76	5.55
Total	2 200 868	100	96.33
M with seq. 1–4.	48 678	82.42	2.13
M with seq. 1–5–4.	4 679	7.92	0.20
M with seq. 1–3.[b]	4 290	7.26	0.19
M with seq. 1–5–5–4.	856	1.45	0.04
(Other)	559	0.95	0.02
Total	59 062	100	2.58
I with seq. 1–3.	13 258	62.69	0.58
I with seq. 1–5–3.	702	3.32	0.03
I with seq. 1.	543	2.57	0.02
I with seq. 1–5–5–3.	432	2.04	0.02
(Other)	6 213	29.38	0.27
Total	21 148	100	0.92
T with seq. 1–3.	2 729	76.87	0.12
T with seq. 1–4.	797	22.45	0.03
T with seq. 1–5–4.	19	0.54	0.00
T with seq. 1–5–5–4.	3	0.08	0.00
(Other)	2	0.06	0.00
Total	3 550	100	0.15

Ordertypes and the sequence codes most frequently generated by them.
[a]The letters L/M/I/T correspond to limit, market, iceberg and market-to-limit order types respectively (cf. Section 2.3 for a detailed explanation of order restrictions).
[b]Market orders are not executed immediately when submitted with restriction to auction phases or during the call phase of the auction. This fact allows for cancellation of market orders. The 1–3 market order sequences found above are of exactly this origin.

3. Analysis of No-fill-deletion Order Lifetimes

3.1 Summary Statistics

Table 6 provides a detailed picture of the lifetimes of no-fill deletion orders (i.e., orders coded with “1–3”), as described in Section 2.4. These no-fill deletion orders embody ∼65% of all order insertions (cf. Table 3).

The lifetimes of the no-fill-deletion orders in Table 6 exhibit a skewed shape. We will investigate this shape further in Section 3.2. The table indicates that the other DAX-30 companies are more or less in the same range. An interesting fact is that the mode value for the no-fill deletion order lifetime of almost all DAX-30 stocks is in the very narrow range of 2.02–2.04 with the only exceptions of Adidas–Salomon, Münch. Rückvers. and Schering with values of 60.01, 0.99 and 60.00, respectively.[3] This pattern might be a first indicator of a large number of orders being

Table 4. Importance of different order types concerning number of orders and money volume traded in the time from 5 to 12 January 2005

	Number of orders submitted[b]				Money volume traded[c]			
Restriction[a]	Limit percentage	Market percentage	MtL percentage	Iceberg percentage	Limit percentage	Market percentage	MtL percentage	Iceberg percentage
None	93.96	2.40	0.16	0.93	80.08	6.32	0.13	8.24
F	0.01	0.00	0.00	0.00	0.14	0.20	0.00	0.00
I	2.34	0.03	0.00	0.00	0.02	0.00	0.00	0.00
S	0.03	0.16	0.00	0.00	4.83	0.03	0.00	0.00
Total percentage	96.34	2.59	0.16	0.93	85.07	6.55	0.13	8.24
In abs. figures	2 200 868	59 062	3 550	21 148	34 841 574 719	2 683 281 921	53 501 579	3 375 360 805

Observation period was the time from 5 to 12 January 2005. A total of 2 284 628 orders were examined. Percentage of the money volume and number of orders belonging to each category are shown above.

[a]Orderrestriction "F" means Fill-Or-Kill, Orderrestriction "I" means Immediate-or-Cancel and "S" means Triggered-Stop-Order.

[b]The left part of the table shows the relative frequency of each order type entered into the Xetra system in conjunction with each order restriction. Hundred percent corresponds to all orders submitted. Thus, in the left part of the table all orders are counted, regardless of whether they are executed or cancelled. The total percentage figures do not sum up to 100% due to rounding effects.

[c]The right part of the table shows the relative amount of money volume traded using each order type in conjunction with each order restriction. Money volume was computed using the size of the execution in shares times the price of the transaction per share. Thus, if the price is better than a possible limit supplied, the transaction price was used for the computation. The cancelled part of any order is disregarded in this part of the table. Hundred percent in the right part of the table corresponds to the total money volume traded on Xetra in the observation period. The total percentage figures do not sum up to 100% due to rounding effects.

Table 5. More actively and less actively traded stocks

Stock	Money volume[a]					Order counts[b]		
	Insertions in €	(partial) exec. in €	% of total	Cancels in €	% of total	# Insertions	# (Partial) exec.	# Cancels
Adidas–Salomon	1 770 215 224	447 125 622	25.26	1 286 488 383	72.67	56 950	17 964	44 821
Allianz	8 790 277 310	2 420 874 661	27.54	6 365 267 254	72.41	139 377	53 282	107 569
Altana	1 246 653 282	327 284 804	26.25	884 871 110	70.98	45 370	18 590	32 164
BASF	5 417 235 455	1 559 059 342	28.78	3 806 098 197	70.26	101 962	41 656	73 566
Bay.Hypo-Vereinsbk.	3 809 997 784	1 440 028 234	37.80	2 420 967 668	63.54	73 804	35 883	53 476
Bay.Motoren Werke	3 514 440 533	1 017 405 425	28.95	2 603 134 296	74.07	85 254	31 886	68 350
Bayer	4 331 672 091	1 499 615 910	34.62	2 800 234 703	64.65	88 208	44 242	59 384
Commerzbank	2 983 413 630	957 340 370	32.09	2 070 980 883	69.42	71 676	32 220	54 939
Continental	2 066 085 303	505 688 538	24.48	1 519 165 870	73.53	56 939	21 832	42 015
Daimlerchrysler	6 127 425 933	1 887 165 222	30.80	4 258 908 966	69.51	106 081	46 882	78 365
Deutsche Bank	9 469 106 165	3 427 840 346	36.20	5 997 248 669	63.33	121 055	60 878	83 319
Deutsche Börse	1 416 524 808	422 635 469	29.84	945 572 830	66.75	34 948	14 174	25 332
Deutsche Post	1 812 172 774	481 907 183	26.59	1 314 871 778	72.56	51 807	21 389	37 590
Dt.Telekom	11 828 478 731	4 943 385 187	41.79	6 709 010 564	56.72	102 992	66 925	60 236
E.ON	7 223 954 037	2 023 701 781	28.01	5 121 734 538	70.90	101 513	46 768	70 762
Fresen. Med. Care	785 318 869	168 525 398	21.46	582 477 219	74.17	30 382	10 302	23 026
Henkel	1 300 108 649	307 276 160	23.63	958 371 953	73.71	54 805	14 370	44 954
Infineon Tech.	2 307 849 938	1 051 246 991	45.55	1 259 620 703	54.58	60 000	35 302	38 333
Linde	1 239 932 379	303 736 968	24.50	893 918 504	72.09	48 285	15 698	38 181
Lufthansa	1 177 439 125	397 502 755	33.76	737 285 375	62.62	42 659	19 028	30 512
MAN	2 369 511 487	542 591 278	22.90	1 789 611 094	75.53	45 841	19 812	33 763

(*continued*)

Table 5. Continued

Stock	Money volume[a]					Order counts[b]		
	Insertions in €	(partial) exec. in €	% of total	Cancels in €	% of total	# Insertions	# (Partial) exec.	# Cancels
Metro	3 051 119 590	961 073 566	31.50	2 033 491 197	66.65	75 733	30 020	55 788
Münch. Rückvers.	6 704 429 897	1 727 628 726	25.77	5 003 312 853	74.63	126 827	40 623	102 038
RWE	5 681 840 719	2 059 831 162	36.25	3 568 859 575	62.81	92 385	54 657	57 242
SAP	9 736 429 511	3 590 803 808	36.88	6 133 401 159	62.99	128 310	72 740	82 167
Schering	3 220 077 589	1 169 923 324	36.33	2 005 412 669	62.28	59 785	34 784	36 808
Siemens	9 617 142 107	2 983 210 594	31.02	6 517 991 136	67.77	117 034	62 447	75 561
Thyssenkrupp	1 803 884 997	599 383 000	33.23	1 148 294 495	63.66	49 433	25 196	33 266
TUI	1 372 789 752	325 475 811	23.71	1 024 373 231	74.62	43 419	18 139	32 086
Volkswagen	3 790 013 654	1 404 451 392	37.06	2 532 581 837	66.82	72 255	41 303	51 283
Total/Average	125 965 541 324	40 953 719 025	30.75	84 293 558 706	68.21	2 285 089	1 048 992	1 626 896

Ranking of the DAX-30 stocks according to money volume traded during the trading days from 5 to 12 January 2005. The top four and the bottom four stocks will be analysed in more detail in the next sections.

[a]Total money volume inserted, traded and cancelled are given in the left section of the table. The cancelled money volume was computed using limit value times number of shares cancelled instead of a real price times number of shares traded.

[b]Count of total orders inserted, orders fully or partially executed and pure cancellations without any execution (“no-fill deletions”) are given in the right section of the table. The usual double counting of money volume applies for the trades. The sum of # (partial) executions and # cancels is greater than the # insertions due to the fact that every partial execution is counted. Therefore, the percentage figures were omitted in the “order counts” section.

Table 6. Summary statistics of the lifetimes of all no-fill-deletion orders from 5 to 12 January 2005

Stock name	Min	1st Q.	Mode	Median	Mean	3rd Q.	Max	*N*
Dt.Telekom	0.07	5.23	2.03	24.09	679.10	106.90	627 500.00	56 038
SAP	0.06	2.96	2.02	11.94	375.40	55.00	620 400.00	75 786
Deutsche Bank	0.06	4.53	2.02	14.69	266.20	55.10	514 300.00	75 891
Siemens	0.07	3.16	2.03	12.43	360.80	54.95	584 700.00	70 202
Allianz	0.05	2.98	2.02	11.16	278.00	46.38	521 400.00	99 937
RWE	0.06	4.67	2.02	22.65	471.80	80.56	532 600.00	52 059
E.ON	0.08	3.50	2.02	14.86	297.50	59.95	629 100.00	64 980
Daimlerchrysler	0.07	4.33	2.02	17.70	338.00	62.09	625 400.00	70 683
Münch.Rückvers.	0.07	4.08	0.99	12.46	240.60	39.59	526 200.00	96 735
BASF	0.07	4.52	2.02	18.29	321.30	60.10	625 600.00	69 632
Bayer	0.07	4.87	2.03	24.14	474.80	88.65	519 900.00	55 017
Bay.Hypo-Vereinsbk.	0.07	6.97	2.03	27.90	437.00	93.74	527 500.00	47 848
Volkswagen	0.08	5.39	2.02	29.54	469.50	95.98	538 300.00	43 147
Schering	0.07	7.10	60.00	38.70	407.30	109.70	529 100.00	34 242
Infineon Tech.	0.08	6.84	2.03	33.06	1 098.00	135.30	622 600.00	34 370
Bay.Motoren Werke	0.06	4.60	2.02	18.04	406.50	60.20	585 800.00	60 642
Metro	0.06	8.65	2.03	24.09	265.10	69.38	610 500.00	52 951
Commerzbank	0.06	4.76	2.02	20.80	469.50	80.47	433 700.00	48 861
Thyssenkrupp	0.08	5.21	2.03	25.46	836.10	108.60	623 800.00	31 008
MAN	0.07	7.59	2.02	34.72	425.80	119.10	584 000.00	31 024
Continental	0.06	7.05	2.02	27.91	351.40	86.08	457 300.00	39 803
Deutsche Post	0.07	5.33	2.03	27.14	474.20	110.00	434 800.00	35 130
Adidas–Salomon	0.07	3.89	60.01	19.41	265.00	67.06	535 800.00	42 332
Deutsche Börse	0.07	4.58	2.03	28.14	307.90	112.10	94 650.00	23 820
Lufthansa	0.06	6.48	2.04	34.68	721.20	132.00	534 900.00	27 915
Altana	0.07	5.82	2.02	33.49	307.60	119.10	432 700.00	30 451
TUI	0.07	5.50	2.02	26.30	433.10	103.00	625 600.00	29 488
Henkel	0.06	4.65	2.03	18.17	192.10	60.23	273 500.00	43 433
Linde	0.07	7.45	2.03	26.54	277.00	84.96	200 200.00	35 791
Fresen. Med. Care	0.07	4.59	2.03	36.81	364.80	132.70	229 800.00	22 066
DAX-30 POOL	0.05	4.58	2.02	19.50	393.50	69.38	629 100.00	1 501 282

Summary statistics of the no-fill-deletion order lifetimes for each stock as well as for the pool of all DAX-30 stocks together are given in the middle columns. All lifetimes were measured in seconds and recorded for orders placed in the time from 5 to 12 January 2005. Total number of observations for each stock are given in the rightmost column.

timed by software programs supporting the human trader or by fully automated trading programs usually termed *algorithmic traders*.

3.2 *The No-fill-deletion Order Lifetime Distribution*

The plot in Figure 1 investigates the distribution of the lifetime of no-fill-deletion orders. To give a precise picture, we differentiate four different time scales. We apply the kernel density estimation[4] procedure to characterize the lifetime frequency.

The spikes in the plots and the overall shape of the plots in Figure 1 reveal, to our knowledge, a previously undiscovered pattern – cancellations occur predominantly after some very "special" lifetimes. At one and two seconds, there is a local maximum. After 30, 60, 120 and 180 seconds there are more such local maxima. Less obvious are the weaker spikes at exactly four, five and

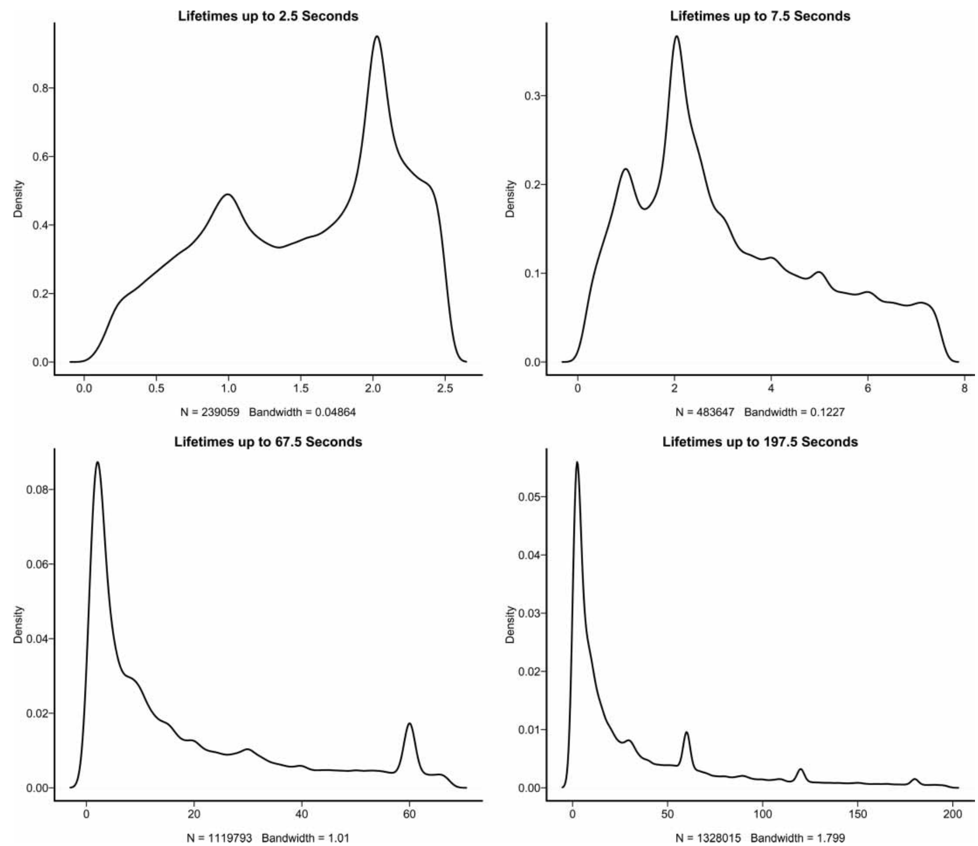

Figure 1. Kernel density estimates for the lifetime of no-fill-deletion orders: We reduced the dataset to the lifetimes contained in the intervals [0; 2.5], [0; 7.5], [0; 67.5] and [0; 197.5] for all DAX-30 stocks to give small scale as well as larger scale pictures of the distribution of order lifetimes. The kernel bandwidth used and the number of orders contained in each interval is given below each of the four graphs, respectively

six seconds. The same pattern can be found for most of the individual stocks of the DAX-30. Figure 2 below illustrates the remarkable similarity in cancellation patterns for the four most actively traded and the five least actively traded stocks given for the range of 0–67.5 seconds.

For the stock TUI, the peak at 60 seconds is not observable (see also Section 3.3.1). The pattern of no-fill-deletion order lifetimes is present throughout the daily trading time. Figure 3 illustrates the observed no-fill-deletion order lifetimes for different subsets of the trading day.

The one-fill-completed orders with a lifetime greater than zero are not terminated by cancellation or execution. The execution of orders is beyond their control, and therefore, not subject to peaking of lifetimes at the end of each update cycle.

3.3 Investigation of Lifetime Peaks at Multiples of 60 Seconds

3.3.1 Example of automated order placements – constant-initial-cushion orders. A closer look at the no-fill deletion orders (i.e., orders with sequence code “1–3”) with lifetimes close to the lifetime peaks shown in Figure 1 gives the following picture. The peaks at multiples of 60 seconds

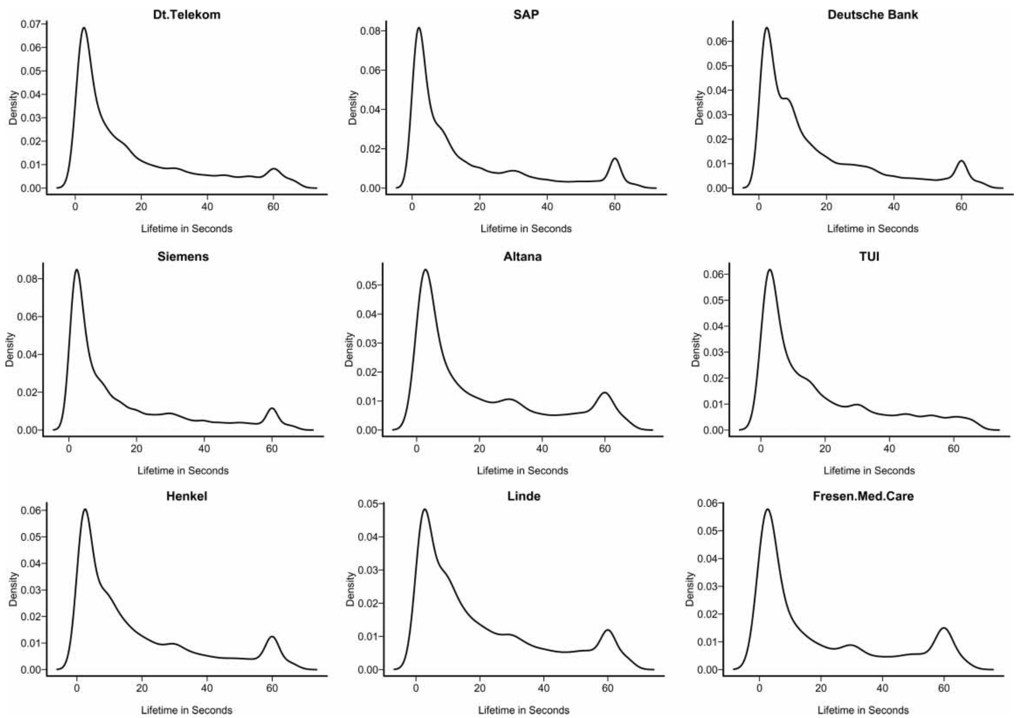

Figure 2. Kernel density estimates for the lifetime of no-fill-deletion orders in the interval [0;67.5] seconds for the most actively traded (Dt.Telekom, SAP, Deutsche Bank, Siemens) and the five least actively traded (Altana, TUI, Henkel, Linde, Fresen.Med.Care) stocks in the time from 5 to 12 January 2005 (cf. Table 5)

can be explained (at least partly) by sequences of orders which we term constant-initial-cushion (CIC) orders.

The orders of such a sequence have the following properties. A CIC order sequence consists of both bids and asks, i.e., of order placements on both sides of the market, where the bids and asks have the same order size. The name “CIC orders” is motivated by the observed order limits. All bids (asks) of such a CIC order sequence have the same constant *cushion* at insertion

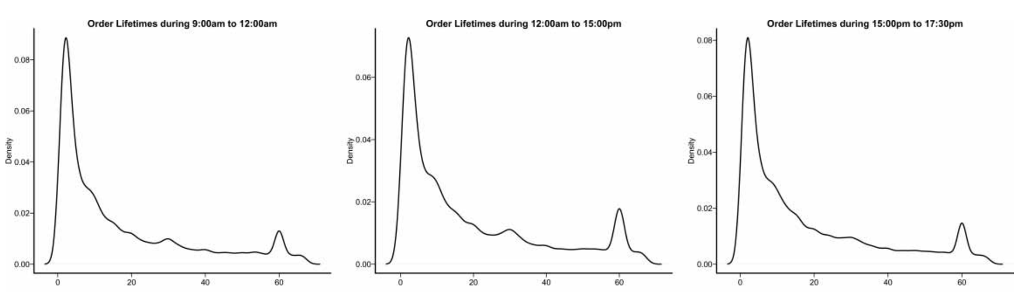

Figure 3. Kernel density estimates for the lifetime of no-fill-deletion orders occuring at daytime 9:00 to 12:00 hours (left plot), from 12:00 to 15:00 hours (middle plot) and from 15:00 to 17:30 hours (right plot). Each plot shows the density for lifetimes in the interval [0;67.5] for all DAX-30 stocks

(*constant-initial-cushion*), where cushion is defined as

$$\text{cushion} = \begin{cases} \text{best bid limit} - \text{bid limit} & \text{for a bid} \\ \text{ask limit} - \text{best ask limit} & \text{for an ask} \end{cases}$$

However, the bids' CIC is not necessarily equal to the asks' CIC. Further, the lifetimes of CIC orders rounded to the nearest second are multiples of 60 seconds. Hence, cancellation takes place only at 60 seconds or multiples of 60 seconds after insertion. In all observed cases, at the time of cancellation the order cushion is not equal to the CIC. Furthermore, for each CIC order with rounded lifetime equal to $l \times 60$ seconds with $l \geq 2, l \in \mathbb{N}$, the following can be said. In all observed cases, the observed cushions at $1 \times 60, \ldots, (l-1) \times 60$ seconds, since insertions are equal to the CIC. The observed cushions at any other point of time during the lifetime of a CIC order are not necessarily equal to the CIC. After a CIC order is cancelled (except for the last bid and ask cancellation in a sequence), a new CIC order is inserted. If a CIC bid (ask) is cancelled, another CIC bid (ask) is inserted at a limit equal to *best bid* $-$ *CIC* (*best ask* $+$ *CIC*).

Table 7 and Figure 4 illustrate a part of a sequence of CIC orders observed for SAP AG on 5 January 2005 between 13:51:36 and 13:56:35 hours. At 13:51:36.00 (at 13:51:35.96) hours a CIC ask (a CIC bid) was inserted with an order size of 1200 shares and CIC of 26 cents. At the time of these insertions, the best bid and best ask were 129.87 € and 129.90 €, respectively. Sixty seconds later, at around 13:52:36 hours, the best bid was still at 129.87 €, while the best ask had moved up to 130.01 €. Therefore, the cushion of the CIC bid remained at 26 cents, while the cushion of the CIC ask decreased to 15 cents. Consequently, the CIC ask was deleted and a new CIC ask was inserted at limit $130.01 + 0.26 = 130.27$ €. The deleted CIC ask had a lifetime of 60.05 seconds. Approximately 60 seconds later, the cushion of both the CIC bid and ask had changed due to the moving best offers. The CIC ask at 130.27 € (CIC bid at 129.61 €) was deleted and a new CIC ask at $130.06 + 0.26 = 130.32$ € (a new CIC bid at $129.90 - 0.26 = 129.64$ €) was inserted. The deleted ask (bid) had a lifetime of 60.03 seconds (120.07 seconds). Hence, the lifetimes of the CIC orders depended on the variability of the best bid and ask (see Figure 4). The lifetimes of the CIC orders shown in Table 7 and Figure 4 varied around 60 and 120 seconds. As the best ask showed higher variation than the best bid in this period (see Figure 4), we observe five insertions on the ask side and only three on the bid side.

In Table 7, CIC orders are illustrated for only a small snapshot of five minutes. To identify all CIC order sequences for a stock we define explicit filtering criteria. In order to avoid data snooping, we used data from 8 to 15 December 2004 to get the defining criteria for CIC orders

Table 7. Sample CIC orders placed on 6 January 2005 for SAP

Time at insertion (hh:mm:ss.cs)	Lifetime (Sec.)	Limit (Euro)	BestBid (Euro)	BestAsk (Euro)	CIC (Euro)	Size	(B)id/ (A)sk
13:51:36.00	60.05	130.16	129.87	129.90	0.26	1200	A
13:52:36.05	60.03	130.27	129.87	130.01	0.26	1200	A
13:53:36.08	59.91	130.32	129.90	130.06	0.26	1200	A
13:54:35.99	60.17	130.28	129.90	130.02	0.26	1200	A
13:55:36.16	59.96	130.20	129.87	129.94	0.26	1200	A
13:51:35.96	120.07	129.61	129.87	129.90	0.26	1200	B
13:53:36.03	120.12	129.64	129.90	130.06	0.26	1200	B
13:55:36.15	59.95	129.61	129.87	129.94	0.26	1200	B

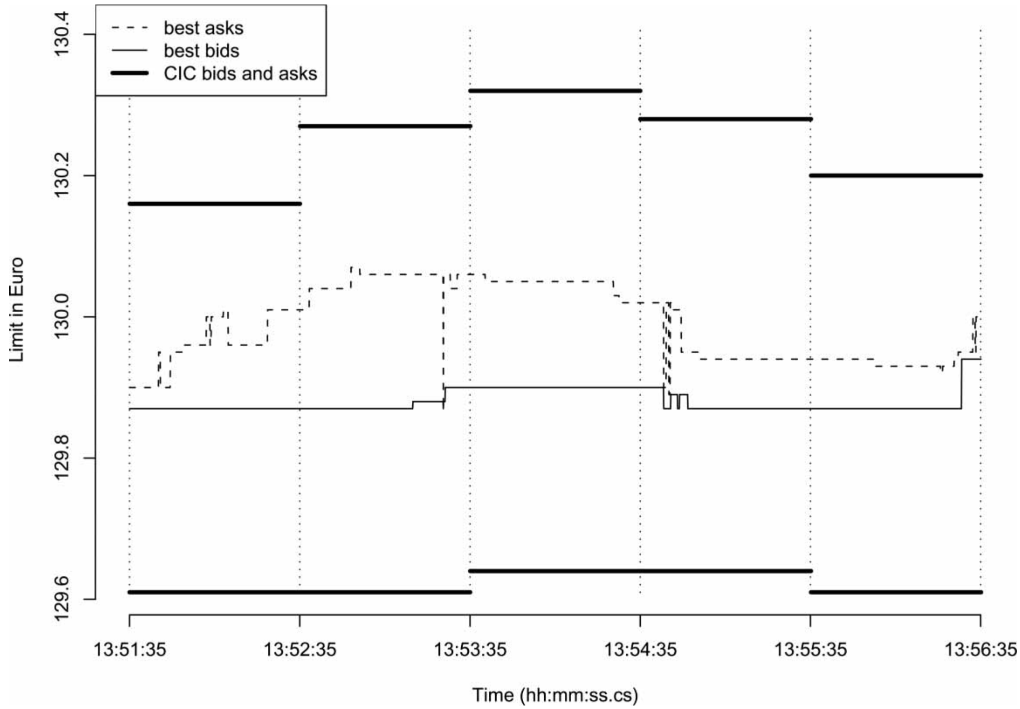

Figure 4. CIC orders for SAP AG on 5 January 2005 between 13:51:35 and 13:56:35 hours with lifetimes of multiples of 60 seconds (dotted lines). If the best bid (thin straight line) or best ask (thin dashed line) changes such that the inserted bid or ask (thick lines) has no longer the CIC at multiples of 60 seconds since insertion, the corresponding order is deleted and a new order is inserted at the CIC. Obviously, deletion only occurs at order lifetimes of multiples of 60 seconds since insertion

and applied them to investigating data spanning the period between 5 and 12 January 2005. The applied filtering criteria for identifying CIC order sequences are given as follows.

1. All orders in a CIC order sequence are no-fill-deletion orders, i.e., orders with sequence code "1–3".
2. A sequence of CIC orders consists of bids and asks. Whenever a bid in this sequence is valid in the order book, an ask of this sequence also has to be valid in the order book and vice versa.
3. A sequence includes at least three orders (i.e., one bid and two asks, or two bids and one ask). Hence, the number of orders in a sequence $N \geq 3$.
4. All bids and asks in a sequence of CIC orders fulfill the following criteria.
   (a) The bids' and asks' cushions at insertion are constant. The bids' cushion at insertion is not necessarily equal to the asks' cushion at insertion.
   (b) The bids' and asks' volumes are constant. The bids' volume is equal to the asks' volume.
   (c) The lifetimes of the bids and asks rounded to the nearest second are equal to or a multiple of 60 seconds.

The result of the application of these filtering criteria to order book data for SAP AG between 5 and 12 January 2005 is given in Table 8. As shown in Table 8, we identified 14 sequences of CIC orders, where the cushions and order sizes of CIC orders for different CIC order sequences

Table 8. All CIC orders placed between 5 and 12 January 2005 for SAP

Period			CIC			Lifetime			
Day (dd-mm-yyyy)	Begin (hh:mm:ss.cs)	End (hh:mm:ss.cs)	Bid (Euro)	Ask (Euro)	Size	Min. (sec.)	Median (sec.)	Max. (sec.)	Number N
5 January 2005	10:00:34.86	14:00:35.73	0.26	0.26	1900	59.68	60.04	419.99	298
5 January 2005	14:14:35.67	14:38:35.89	0.18	0.49	1200	59.84	59.99	120.06	27
5 January 2005	14:45:35.99	15:47:36.33	0.26	0.26	1900	59.86	60.04	299.88	91
5 January 2005	15:53:36.41	15:58:36.47	0.26	0.26	1000	59.90	60.02	60.08	10
5 January 2005	16:05:36.68	16:36:36.50	0.16	0.55	1100	59.72	60.02	239.52	24
5 January 2005	17:15:36.91	17:26:36.88	0.18	0.49	1300	59.86	60.06	119.90	15
6 January 2005	10:02:34.68	17:28:37.30	0.26	0.26	1200	59.70	60.06	419.84	580
7 January 2005	10:00:35.33	14:28:36.72	0.27	0.27	2200	59.72	60.03	840.23	340
7 January 2005	14:51:36.95	17:28:37.64	0.26	0.26	1700	59.68	60.01	239.60	181
10 January 2005	10:01:35.52	17:27:37.91	0.28	0.27	1100	59.74	60.06	360.08	567
11 January 2005	11:36:13.38	16:00:15.14	0.26	0.26	1700	59.78	60.04	300.03	354
11 January 2005	16:27:15.50	17:27:15.93	0.26	0.26	1000	59.73	60.02	120.30	61
12 January 2005	10:05:35.66	15:47:38.22	0.25	0.25	1700	59.61	60.04	480.19	422
12 January 2005	16:01:38.02	17:27:38.23	0.25	0.25	1600	59.64	60.01	120.18	136

varied. Between 5 and 12 January 2005 the order size varied between 1000 and 2200 for SAP. The CIC ranged between 16 and 27 cents for the CIC bids and between 25 and 55 cents for the CIC asks for SAP. The maximum lifetime of a CIC order was 840.23 seconds. For all CIC orders we find rounded lifetimes of 60 seconds and multiples thereof. A technical reasoning for the marginal fluctuations in CIC order lifetimes is given in Section 3.5.

A possible explanation for these observations of CIC order sequences may be that an automated order placement system updates CIC orders at intervals of 60 seconds by cancellation and subsequent insertion such that the orders' cushions fulfills the properties described above. A further look at the order book suggests that the intraday change of the order volume or cushions for the CIC orders is because of the order matching of a CIC bid or ask. At the end of each of the indicated periods (excluding end of day periods) shown in Table 8, we find executed orders, each with an insertion time equal to the deletion time of the last observed CIC order in the corresponding sequence. Further, each of these executed orders has the same cushion and order size as the last deleted CIC order of the corresponding sequence.

However, the dataset does not allow us to identify the order submitting trader. Therefore, we cannot make a definite statement about these suggestions. In the next section, we further substantiate our explanations by investigating all 30-DAX stock for the occurrences of CIC order sequences.

3.3.2 CIC order statistics for all DAX 30 stocks. Table 9 shows footprints of CIC order insertions for almost all DAX-30 stocks. The cushion ratio shown in Table 9 expressing the cushion as a percentage of the median price observed between 5 and 12 January is around 0.2%. A lower bound for the bid and ask cushion is observed at 4 cents for most of the DAX stocks. The existence of an absolute lower bound on the cushion would explain the high cushion ratios for stocks with low median prices such as Lufthansa and Infineon. On the basis of this observation, one can approximate the cushion for each stock by $\max(0.2\% \cdot \text{Median Price}, 0.04)$.

Table 9. CIC orders for all DAX30 stocks observed between 5 to 12 January 2005

	Bid CIC		Ask CIC		Lifetime			Size			Money Volume[b]		Price[c]	Size[d]
	Median (Euro)	Ratio[a] (%)	Median (Euro)	Ratio[a] (%)	Min. (sec.)	Median (sec.)	Max. (sec.)	Min.	Median	Max.	Abs. (Tsd. Euro)	Rel. (%)	Median (Euro)	Median
Dt. Telekom	0.04	0.24	0.04	0.24	59.56	120.05	1 860.12	8900	11 900	15 000	248 779	4.34	16.53	4500
SAP	0.26	0.20	0.26	0.20	59.61	60.04	840.23	1000	1700	2200	625 098	12.09	129.78	250
Deutsche Bank	0.13	0.20	0.13	0.20	59.51	60.07	780.11	1900	2900	4400	502 989	10.09	66.33	586
Siemens	0.12	0.19	0.12	0.19	59.51	60.07	1 439.89	2000	3300	4800	449 210	7.93	61.95	1000
Allianz	0.19	0.20	0.19	0.20	59.64	60.05	540.05	100	1600	2700	486 106	8.69	96.48	300
RWE	0.09	0.21	0.09	0.21	59.51	60.10	900.17	100	5500	7200	361 828	11.79	43.05	690
E.ON	0.13	0.19	0.13	0.19	59.54	60.07	960.14	2300	2900	4900	444 115	9.92	67.01	800
Daimlerchrysler	0.07	0.20	0.07	0.20	59.68	60.14	1 140.18	4300	6700	8300	408 159	11.20	35.82	860
Münch.Rückvers.	0.19	0.21	0.18	0.20	59.58	60.07	1 080.14	1300	1700	3000	461 495	10.35	92.27	200
BASF	0.11	0.21	0.10	0.19	59.58	60.10	840.20	2300	3000	5500	419 634	12.68	52.43	500
Bayer	0.05	0.21	0.05	0.21	59.50	119.78	2 160.04	5200	6700	10 000	250 767	10.71	24.05	814
Bay.Hypo-Vereinsbk.	0.04	0.23	0.04	0.23	59.71	119.90	4 200.32	4700	8200	15 000	216 155	10.59	17.04	900
Volkswagen	0.07	0.20	0.07	0.20	59.62	60.17	1 199.90	200	5400	8100	246 830	11.56	35.89	500
Schering	0.11	0.20	0.11	0.20	59.53	60.08	1 259.96	1300	2200	3500	296 413	18.39	54.10	370
Infineon Tech.	0.04	0.51	0.04	0.51	59.52	179.89	5 520.38	8000	12 200	15 000	84 426	8.35	7.86	1200
Bay.Motoren Werke	0.07	0.20	0.07	0.20	59.53	60.22	1 980.17	200	5600	8200	346 582	15.47	34.30	400
Metro	0.08	0.19	0.08	0.19	59.55	60.15	2 220.24	1800	3200	6000	203 185	11.55	41.30	200
Commerzbank	0.04	0.25	0.04	0.25	59.66	119.99	2 700.33	6300	7400	14 400	175 417	10.03	16.09	800
Thyssenkrupp	–	–	–	–	–	–	–	–	–	–	–	–	16.31	800

(*continued*)

Table 9. Continued

	Bid CIC		Ask CIC		Lifetime			Size			Money Volume[b]		Price[c]	Size[d]
	Median (Euro)	Ratio[a] (%)	Median (Euro)	Ratio[a] (%)	Min. (sec.)	Median (sec.)	Max. (sec.)	Min.	Median	Max.	Abs. (Tsd. Euro)	Rel. (%)	Median (Euro)	Median
MAN	0.06	0.20	0.06	0.20	59.62	119.88	1 560.17	1000	1400	2100	68 880	4.26	29.35	200
Continental	0.10	0.21	0.10	0.21	59.51	60.18	1 079.99	1200	2100	2900	165 254	12.52	48.31	200
Deutsche Post	0.04	0.24	0.04	0.24	59.58	120.10	2 520.25	400	8300	13 800	195 333	17.09	16.97	900
Adidas-Salomon	0.24	0.20	0.24	0.20	59.52	60.08	1 800.02	100	400	1400	128 004	11.50	118.51	100
Deutsche Börse	–	–	–	–	–	–	–	–	–	–	–	–	44.74	200
Lufthansa	0.04	0.38	0.04	0.38	59.52	120.14	2 760.26	6100	8500	12 300	101 180	16.87	10.65	800
Altana	0.10	0.22	0.09	0.20	59.55	119.74	1 860.28	100	1400	2700	105 566	13.43	45.13	200
TUI	–	–	–	–	–	–	–	–	–	–	–	–	18.09	300
Henkel	0.13	0.20	0.13	0.20	59.52	60.13	2 220.30	100	900	1300	123 841	14.66	66.44	114
Linde	0.10	0.21	0.10	0.21	59.62	119.74	2 100.10	100	1200	2000	72 297	9.20	48.23	163
Fresen.Med.Care	0.12	0.21	0.12	0.21	59.52	60.29	1 620.16	300	600	900	49 165	9.85	58.05	130

Stocks are ordered according to traded money volume.
[a]The cushion ratio is calculated as cushion divided by the median price.
[b]The price is calculated as the median of all prices observed between 5 and 12 January for each stock.
[c]The total money volume is given in absolute terms (in thousands) and as fraction of the total money volume of all no-fill-deletion orders for the stock.
[d]Size is given as the median of the inserted order size of all no-fill-deletion orders.

For Deutsche Börse, Thyssen Krupp and TUI the rows in Table 9 are empty, because CIC orders are not identifiable for any of the three companies. This observation is consistent with the result reported in Figure 2, where for TUI no significant lifetime peaks for 60 seconds could be found. The lifetime distribution of Deutsche Börse AG and Thyssen Krupp, which are not plotted here, exhibit similar lifetime distributions lacking significant peaks at multiples of 60 seconds.

The volumes of the CIC orders are multiples of 100 shares. Stocks with a cushion equal to 4 cents have the highest maximum volumes ranging between 12 500 and 15 000 stocks. The maximum volume of 15 000 stocks was observed for Deutsche Telekom, Bay. Hypo Vereinsbank and Infineon. Comparing the median CIC order volume with the median order volume of all no-fill-deletion orders shows a higher average volume for CIC orders.

The maximum lifetime of CIC observed ranges between 540 and 5220 seconds. The overall maximum lifetime of 5220 seconds was observed for Infineon for both the CIC bid and ask inserted at 12:46:35 hours and cancelled at 14:18:35 hours on 5 January 2005. During this period in which the intraday auction also took place (see Section 2.2) the best bid and ask remained the same. The stocks with CIC order cushion equal to 4 cents all have a median lifetime at around 120 seconds. Infineon has an even median lifetime of 179.89 seconds.

The column *Money volume* in Table 9 shows that CIC orders represent between 4.3% and 18.4% of all no-fill-deletion orders observed between 5 and 12 January 2005.

3.4 Trading Strategy Behind CIC Orders

The trading strategy behind the placement of CIC orders closely corresponds to the limit order trading pattern investigated in Handa and Schwartz (1996). The authors of that paper suggested placing a network of bid and ask limit orders with cushions of 1%, 2%, 3%, 4% and 5% and revising the limit orders and placing a new network of limit orders upon each execution. They tested the strategy for the DOW-30 stocks and found significant positive returns from resulting roundtrip trades. The CIC strategy differed insofar as it used a different cushion size (0.19%–0.51% cushion instead of 1% cushion in Handa and Schwartz (1996)) and periodic updates instead of updates only upon order execution.

3.5 Distribution of CIC Orders Lifetimes

The lifetimes of CIC orders reported in the previous sections are not exactly equal to multiples of 60 seconds, but vary within a range of approximatlely one fourth of a second. Figure 5 shows the observed lifetimes of CIC orders plotted as histograms and fitted to normal distributions with sample means equal to 60.01 and 120.01 seconds and sample standard deviation of about 0.11 and 0.12 seconds, respectively.

Both lifetime distributions deviate from the Gaussian distribution and are leptokurtic. For both distributions the Kolmogorov–Smirnov test rejects the normality hypothesis at the 1% significance level.

The peak around, e.g., 60 second lifetimes for CIC orders might lead to the conclusion that computer software updates orders on the basis of a 60 seconds lifetime. However, periodic updates inside the exchange might not explain the fluctuations around the order lifetime of 60 seconds.

A factor that might cause the fluctuations around 60 seconds is the electronic network connecting the exchange with exchange members. We assume that all signals are generated inside the exchange member group. If we assume that the signals are transmitted through an electronic

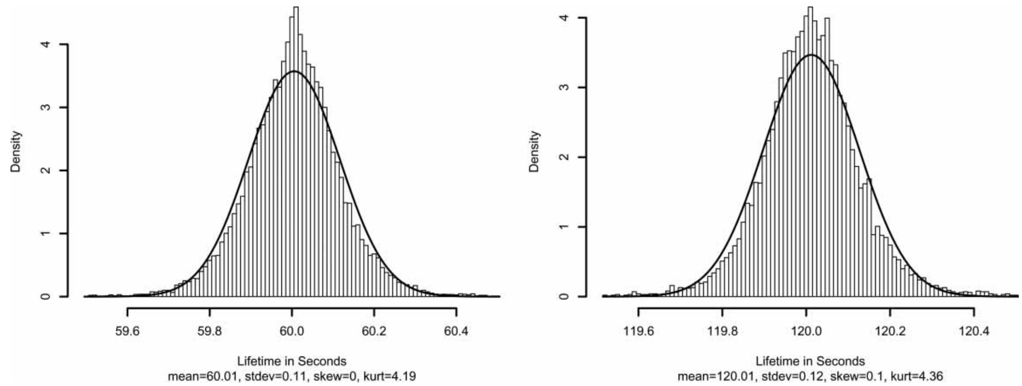

Figure 5. Lifetime distribution of observed CIC orders for all DAX stocks (except for Deutsche Börse, TUI and Thyssen Krupp) placed between 5 and 12 January 2005 (histogram). The thick line represents the normal distribution with estimated parameters $\hat{\mu}$ = mean and $\hat{\sigma}$ = stdev. Sample kurtosis (kurt) and skewness (skew) are given

network and might have to travel longer distances, then this might explain some of the order lifetimes' fluctuations – usually a real-time data feed provided by the exchange (or other companies specializing in providing data) transmits input to the exchange member. The exchange member reacts and enters a new order at time $T1$. The signal travels through the network and arrives at time $T2$. The time spent on the way to the exchange might be subject to possible network delays. The timestamp on the order is generated in the exchange and therefore already carries the delay that has occurred from $T1$ to $T2$. After a fixed time interval, like 60 seconds, counting from time $T1$, the exchange member updates its positions. Let us assume that it decides to cancel the order. A signal is then emitted at time $T3$. The signal again travels through the network layer and arrives at time $T4$ in the exchange. Another timestamp is recorded at arrival. This timestamp again already contains the delay that occurred between $T3$ and $T4$. If the network speed is not constant, but subject to perturbations, then this would generate variation in the order lifetime from $T2$ to $T4$, even when the time between $T1$ and $T3$ is always 60 seconds or a multiple thereof.

It is a well-known fact among network specialists that latency distribution of network traffic usually exhibits an approximately Gaussian shape. There are papers documenting that even very few participants in the network are usually sufficient for the network traffic time distribution to exhibit Gaussian features (cf. Meent *et al.* (2006)). Deviations of the network traffic distribution from Gaussianity is treated, for instance, in Jin *et al.* (2002).

Hence, the delays might be a simple consequence of communication via the electronic network media. Such a conclusion suggests that further investigations of the electronic infrastructure of a market place and the remote market participants might be necessary, as this might be of relevance with respect to best execution issues.

4. Summary

Our findings indicate the existence of previously undiscovered patterns in the order book's structure when investigating the second and sub-second range of no-fill-deletion lifetimes. Bearing in mind that this range is nowadays the time frame that professional traders and algorithm designers have to cope with we investigate these patterns on an order-by-order basis, i.e., by analysing relevant orders and the corresponding detailed order event entries in the order book.

In more detail, we analyse all no-fill-deletion orders with lifetimes equal to multiples of 60 seconds and detect sequences of orders, which we term CIC orders. In order to avoid data snooping, we analysed the data from 8 to 15 December 2004 to get the defining criteria for CIC orders and applied these criteria for filtering and investigating data spanning the period between 5 and 12 January 2005. The distance at insertion of a CIC bid (ask) limit to the best bid (ask) limit is about 0.2% of the median price for most of the 30-DAX stocks. Our investigation leads us to evidence of activities of automatons trading on the buy and sell side, seemingly fishing for roundtrip trade opportunities in a fashion similar to that described in Handa and Schwartz (1996). Thus, our analysis of the CIC orders has shown that results from the academic literature are implemented in modern algorithmic trading systems and now influence some of the algorithmic behaviour on Xetra. It also illustrates that at least a significant part of the order flow can be explained explicitly by analysing certain groups of orders for strategies executable by algorithms.

A further observation is that the lifetimes of CIC orders are not exactly equal to multiples of 60 seconds, but vary in the range of a few hundredths of a second. This might give an indication of the influence of variations in the speed of the electronic network connecting the exchange with exchange members. Such a conclusion suggests to further investigate the electronic infrastructure of a market place and the remote market participants, as this might be of relevance with respect to best execution issues.

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Notes

1 The time span from the moment an order is generated in the electronic system of an exchange member to the time when a confirmation signal from the exchange arrives back at the order submitter is called *roundtrip time*.

2 In our dataset containing all order entries of all DAX-30 stocks between 8 and 15 December 2004 and between 5 and 12 January 2005, such a volatility break occurred only twice.

3 For a treatment of cancellations with lifetime lesser or equal two seconds, see Hasbrouck and Saar (2005).

4 Intuitively, kernel density estimates can be understood as histograms with infinitely fine classes smoothed by moving averages. Formally, kernel density estimates are functions of the form

$$f(x) = \frac{1}{n}\sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right),$$

where K is the kernel function. For all plots in this paper, Gaussian kernels were used, i.e., all kernel density plots use the formula

$$f(x) = \frac{1}{n}\sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right), \quad \text{where} \quad K(u) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}u^2\right).$$

For an extensive comparison of the properties of different kernels see Hwang *et al.* (1994).

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