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# Empirical Insights on Financial Intermediary Services – How Order Slicing and Modification impacts Order Executions Times

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**Abstract.** Information Technology heavily transforms the financial industry and already changed the intermediating services of brokers. This class of service providers has to fulfill the trading of especially large orders with best possible executions and within a given time frame. Based on previous research in order executions, we develop a model for survival analysis of orders and estimate the influence of multiple factor groups and various factors in these groups to estimate how slicing, modification and the overall specification influence the likelihood of execution. Using a unique message-based dataset of Deutsche Boerse AG, we find empirical evidence on the influence of factors whether brokers and their traders can execute the overall order in a definable time frame. Finally, we discuss the observed coefficients and show how brokers and their traders can use and aggregate these coefficients for decision-support on how to slice modify and specify large client orders.

**Keywords:** Service Science, Intermediation, Survival Analysis, Brokerage, Order Management

## 1 Introduction

The use of technological advances, which enhance and create service systems, results in the fact that technology becomes embedded into value co-creation, so that customers, service providers, and often society at large can benefit from it [1]. More specific, services are collaborative processes, which create value in their specific context [2], [3]. The financial industry is such a section that creates value, which is explicitly measurable in monetary measures. Lucas et al. posit that technology heavily transformed economic sections like the financial industry [4]. The experience with these technologies has moved financial markets from making phone calls to the usage of a full-service broker when trading electronic orders [4].

This paper investigates the service that brokers provide for their customers. Brokers are intermediaries that charge commission fees for handling the order flow of investors towards the financial market [5]. They offer their expertise in trading and thus provide customers advice on how to implement their investment decisions [6].

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This is realized by the arrangement of trades for clients in the financial industry and by the support of matching buy and sell orders [6]. Brokers try to achieve best possible order matching for their clients [5]. European brokers are even forced to provide best execution by the EU commission [7]. This intends to foster competition between financial service intermediaries and lowers overall trading costs.

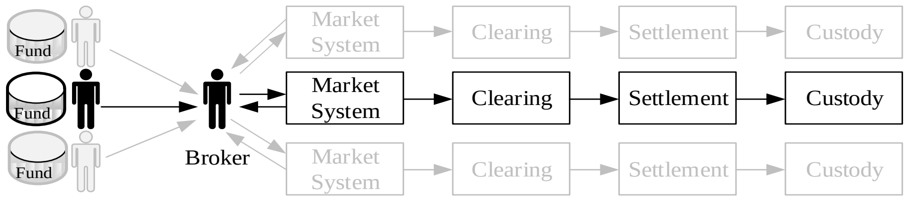


**Fig. 1.** Process flow from client to broker, market systems and downstream systems

When a broker receives a big client order, he has to decide, depending on its size, how to favorably split the order into sub-orders and whether to delegate it to one or multiple market systems (cf. Fig. 1). As downstream activities are determined by the selection of the market, we shall rigorously evaluate patterns and components of the information-intense interaction between the broker and the market system [1]. The broker has to decide how to slice orders into the market within the given time frame and if market conditions change also whether and how to modify the open orders at the market. This evaluation shall focus on critical interactions with service systems [1]. Bearing this in mind we pose the following three research questions in the context of financial broker services:

1) *How does the specification of electronic orders influence the execution likelihood?*
2) *How do modifications of electronic orders influence the execution likelihood?*
3) *How can electronic orders be managed, sliced and adjusted to be exectuted more likely?*

The structure of the paper is as follows: First we give an overview of related Information Systems (IS) and Finance literature (section 2). In section 3, we introduce our general research setup and the order lifecycle that we analyze. Based on previous work we derive hypotheses on how various factors influence order survival in a market. With these constructs and variables, we describe our analysis process and the resulting hazard function model. We present the descriptive and empirical results in section 4. These results are discussed in relation to their contribution to research and practice. There, we explain how the empirical results can be applied as a framework for order slicing and modification. Finally, we highlight potential limitations and conclude (section 5).

## 2 Theoretical background

Related work in this field of research is two-fold: First, we will present related work that was done in IS research for the field of order management in the financial markets. Second, we give insights to additional work from the field of Finance and Market Microstructure that support understandability and help to define the research design.

### 2.1 Related Information Systems Research

Maglio et al. underline the importance of service systems within the discipline of information systems research [8]. Weitzel et al. postulates that good, coordinated, and uninterrupted straight-through-processing (STP) increases efficiency and reduces costs in the financial industry [9]. Applied to order handling this gives indication that less modification and better slicing should be beneficial for the order handling of a broker. Muntermann et al. analyze the order processing times in the middle-office of a European investment fund [10]. They find that order processing times are influenced by the fund manager, his brokers and custodian, the middle-office employees and systems as well as the specific weekday. Ende et al. analyze latency reducing technologies and their influence on how favorable orders are executed. Evidence is given that for every percent less latency the likelihood of unfavorable order book changes shrinks by 0.9 percent. This implies that a timing optimized trading setup has direct influence on the quality of potential execution prices of an order [11].

Gsell and Gomber analyze electronic orders to analyze the behavior of algorithmic traders. They find that algorithms are more active and more aggressive in the market then human traders. They conclude that algorithmic traders use their technological setup to monitor the market and to specify orders appropriate to this information [12]. Groth provides an empirical analysis whether algorithmic traders increase uncertainty in terms of higher price volatility. As result, evidence is given that algorithmic traders and human traders have an influence on volatility, but that neither human nor algorithmic traders increase volatility [13]. Both recent studies use a message-based dataset to investigate the order flow of algorithmic and human traders.

### 2.2 Related e-Finance and Market Microstructure Research

Hendershott and Riordan use a message-based dataset from Deutsche Boerse AG to analyze the influence of algorithmic trading on liquidity of limit order books. They find empirical evidence by showing that trading becomes less aggressive when the situation is expansive and more aggressive when the situation is cheap. They also find that algorithms place more efficient limits and execute more efficient prices [14].

Chatterjee and Mukhopadhyay apply an order survival analysis by using order book snapshots and the concept of hypothetical orders. They find that the aggressiveness of an order mostly explains the likelihood of open orders to be executed in the order book [15]. Aggressiveness is the absolute percentual ratio of the midpoint of the bid/ask-spread and the order limit price. Similar studies investigate how the general market situation affects the execution probability of limit order:

Omura et al. find that execution probability is low when the order book is thick and an order is priced relatively less aggressive [16]. Lo et al. analyze that the execution time is determined by the limit price and less by the order size [17]. Cho and Nelling reveal that aggressive orders are more likely to be executed and results shall be controlled for buy and sell orders independently [18]. Similarly, Ranaldo analyze the execution times orders depending on their aggression in the limit order book [19].

Gava find that execution times are shorter in the beginning of the day and when they are more aggressive [20]. Al-Suhaibaini and Kryzanowski reveal execution likelihood is higher when limits are priced reasonably [21].

Related work in the field of Finance and Market Microstructure shows that the relation of order aggressiveness and market situation is well-investigated. Previous studies on order survival (except from order aggressiveness) lack information on how orders are specified. Thus, they cannot give evidence or support for broker and traders that have to specify their orders and sub-orders. Consequently, financial service intermediaries cannot rely on these studies to specify and slice orders so that is likely to have these orders executed within the given amount of time. This is why we focuses explicitly on parameters that the trader can influence and shall give trader decision and design support on how to optimize the order execution likelihood and to make good decisions independent for the current and unknown future market situations.

# 3 Methodology

## 3.1 General Research Setup

In this study, we setup an empirical analysis on order survival due to the trader's order specification. Thereby, we do not only try to find empirical evidence on the relation between specification and survival, but also use the evidence to give traders a handy framework on how to design orders for a specific execution likelihood. Previous mentioned research in Market Microstructure (cf. section 2.2) tries to explain how certain levels of liquidity and volatility affected orders in the market. This can be observed, but not influenced or modified by the trader during the lifetime of the order.

To receive the raw influence of order size specific slicing and modification, we filter the effects of other order parameters by introducing them as control variables into the model. We perform our empirical analysis for this model on a firm-independent dataset, which includes the behavior of all traders that trade the 30 highest-liquid German stocks on the only electronic spot market system in Germany. Motivating the research model, we give a brief introduction on constructs in this field of research, before we define our model variables and derive hypotheses on how this variables influence order survival.

### 3.2 Order Lifecycle Model in Electronic Equities Trading

Schwartz and Francioni outline the trading process along the securities value chain as follows [5, p.44]: ‘Information is the input that drives investment decisions and therefore trading. Securities prices are a result (output) of the process.’ This investment decision is made by a fund manager (also called ‘buy-side’ investor) who delegates the execution of trading task to a broker (also called ‘sell-side’ intermediary). The fund manager communicates his trading decision to buy or sell shares of a stock to the broker and defines with him a strategy on how to trade the order (cf. Fig. 2 left).

Based on this strategy the broker decides how to specify orders or multiple so-called sub-orders and to send them to the market(s). In this case study, we specifically focus on lifecycles of orders in the electronic trading system Xetra of Deutsche Boerse AG, but the general market setups and their principals are very similar for all European stock exchanges. As bigger orders create market pressure, which can shift the market price while trading in the market [6], traders try to slice orders into smaller sub-orders causing less market pressure and consequently less market impact. These orders are sequentially sent to the market and can be adjusted and modified, if the market situation changes over time. Especially when the trader plans to send the overall order to the market, then the given specification restricts and defines how the market can be affected. The trader tries to optimize the slicing of his orders in such a way that the market impact declines on the one hand, but also that the order is likely to be executed before unfavorable events in the market might affect the execution price of the overall order [5].

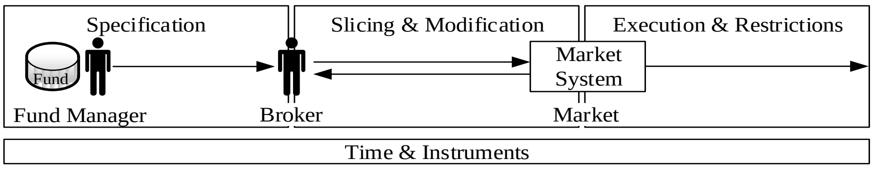


**Fig. 2.** Trading and order lifecycle model

If the trader recognizes that the situation becomes unfavorable, then he can modify the sub-orders specification. As open orders in the order book are waiting in a queue with price/time priority, modifications that increase the order volume provide traders an unfair, queue-jumping advantage. To keep the market fair for all market participants, the Xetra system resorts an explicitly modified order to the end of the queue of orders with the same limit and thereby increases the implicit waiting time for execution according to the priority dimension time [22].

The Xetra trading system also checks whether the order has a restricting specification that holds an order back from immediate (partial or full) execution. This can be a given limit, but also requirements like order restrictions or trade restrictions. A trade restriction can be, e.g. a condition that an order shall be canceled, if it is not immediately executable. A trade restriction can enforce that an order shall just be executed in a specific trading phase (like the continuous trading or the auction phases of Xetra). If an order can be traded partly or full within its limit price and its other restrictive con-

5

ditions, then the order becomes marketable and the Xetra system executes the order and notifies the counterparts and the clearing system for bookkeeping on the trades.

Due to the time and the instruments traded, the likelihood of execution can vary. Focusing on our research questions, we investigate influences of the specifications, executions, restrictions, time and instrument to the lifetime time of an order in the electronic order book of Xetra.

### 3.3 Influencing Factors and Hypotheses

**Slicing & Modification**

If an order is relatively larger than the average order in the market then it is likely that it will be matched against multiple smaller orders. To estimate how to slice an order, and how to set the sizes of sub-orders, we measure the influence of partial executions as they are a good proxy for the multiples that an order is bigger than the average limit order. Thus, we add a variable to our model that counts the partial executions per order before its complete execution (*PartCount*).

Weitzel et al. postulate that an uninterrupted STP enhances the efficiency of a process [9]. That is why we add the number of explicit modifications (*ModCount*) to an open order as a variable to our model and estimate their magnitude of influence to the execution likelihood of an order. *That is why we expect that slicing and modification can increase the lifetime of orders in the order book.*

**Specification**

Chatterjee and Mukhopadhyay give evidence that the closer the limit is set to the midpoint of the bid-ask-spread, the higher the likelihood of a fast execution will be (*Aggressiveness*) [15]. Lo et al. show that the execution probability is not sensitive to the size of an order (*OriginalOrderSize*) [17]. The same is analyzed for the *HiddenOrderSize*, if the order is not an *IcebergOrder* that lowers the likelihood [23].

Hasbrouck and Saar find that co-located trading (*isColocated*) decreases spreads and has a higher likelihood to be executed [24]. Cho and Nelling highlight that momentum can bias results and analyses should be controlled for the BuySell direction (*isBuy*) of an order [18]. Gsell and Gomber as well as Groth find that automatic traded orders (marked as relating to the so-called automated trading program (*isATP*)) have in general shorter survival times for both executions and deletions [12]. *That is why we create controls for the mentioned variables and expect those to have mixed influences on how long an order will stay unexecuted in the order book.*

**Execution & Restrictions**

Gsell and Gomber find that, on average, deletions by the user occur earlier than executions [12]. That is why we add the last message type of an order lifecycle as dummy to our model (*Execution*, *DeletionByUser*, *DeletionBySystem*). Schwartz and Francioni highlight that a typical trading day has several phases [5]. A restriction to trade just in a specific phase lowers the likelihood of getting an order executed. So, we mark *MainTradingOnly* and *AuctionOnly* phase restriction by dummy variables.

Harris shows that restrictions to orders have negative influence to the execution likelihood [6]. That is why we include dummy variables to our model that mark if an order has typical restrictions like *ImmediateOrCancel* or a second restricting limit like a *TriggeredStopOrder*. *That is why we expect that control variables on executions and restrictions will extend the duration on how long orders wait to be executed*.

**Time and Instruments**

Gava shows that the time of the day impacts the likelihood of order execution [20]. That is why we add the specific trading day and the specific hour at order submission as control variable to our model. Lo et al. find that individual stocks and their price levels have specific influence to the survival time of an order in an order book [17]. That is why we add dummy variables for each instrument identified by the international securities identification number (*ISIN*) as a proxy for price levels. *So we expect the instrument- and the time-specific control variables have mixed influence on the lifetime of submitted orders.*

### 3.4 Process Analysis

To evaluate the lifetime of orders in the Xetra order books, we analyze and aggregate a very unique dataset that we received from Deutsche Boerse AG. This dataset logs all events that affected the limit order books of Xetra for DAX 30 instruments within March 2nd and March 13th, 2009. The order limit lifecycle is measured as the time span from the submission of a non-marketable limit order (immediately marketable orders are neglected in the following analysis as they do not have a survival time in the order book) till the deletion or full execution of the order. The underlying order book structure was not fully-reconstructed as it is not needed for the given research questions. This would require special indices that are missing in the available data.

The dataset consists of 55,679,988 single events that affected the Xetra market system. Nineteen non-marketable market orders were deleted as these might have given a biased representation of market orders, as market orders normally do not reside in the order book in the phase of continuous trading.

To investigate the survival time of orders in the order book a hazard function model regression [25] is selected. This supports the non-linear behavior of survival times as well as the strict positive characteristics of the model variables and avoids broken assumptions compared to a linear regression [25]. These hazard function models have been applied to analyze influences strike duration, divorce rates, length of studies and pensions and mortality expectations in social science [25] and are in general designed to estimate how long an entity will stay in a certain state.

The hazard rate ($\lambda$) is the likelihood at which order $i$ resides in the order book for a given period without being deleted or executed. The model estimates the likelihood with given influencing factors and allows to estimate direct influences to the survival time. Thus, if the model estimates a positive coefficient then the likelihood of longer order survivals increases in the percentage value of the coefficient and vice versa. The coefficients show changes in likelihood relative to the average limit order. That is why we expect that the order lifetime is dependent to their influencing factors:

$$OrderLifeTime(t) = OrderLifeTime_0(t)\ exp\ (\beta_1\ SlicingModifications + \beta_2\ Specifications + \beta_3\ ExecutionRestrictions + \beta_4\ TimeInstruments_4)$$

As the error rates decrease over time (longer processing times are much less likely than shorter ones) we expect a Weibull distribution of the order *OrderLifeTime* (positive random variables and not normal-distributed) that is also often used in previous research [26] and validate this assumption with the descriptive statistics in the next section. $OrderLifeTime_0$ is the unknown execution function without further influences.

# 4 Data and Empirical Results

## 4.1 Dataset and Descriptive Statistics

Our final dataset consists of 1,000,155 fully reconstructed order lifecycles including the total residence time and variables for slices and modification, order specification, order execution and control variables for weekday, daytime hour and 30 instruments for 10 trading days. All *OrderLifeTimes* are measured in milliseconds and the average processing time is around 40 seconds (40,452ms). The median is 1,270ms. 95% of the orders reside in the order book no longer than 81,520ms. After 4min, 98% of the orders no longer reside in the order book. And 99% of the orders do not persist more than 8min in the order book.

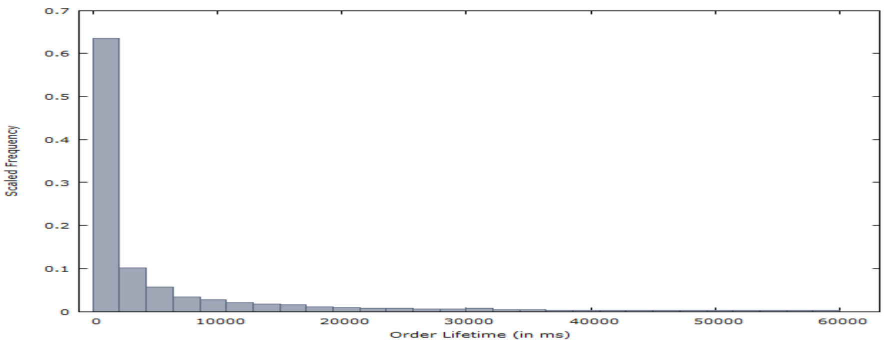


**Fig. 3.** Frequency distribution of order lifetimes measured in milliseconds in the first minute after the order submission. Plot cropped after the first minute to enhance readability.

On the one hand, the fastest order lifecycle is measured with 1ms (due to time stamp precision), while on the other hand, the longest order lifecycle took 27 days ($9.9458*10^7$ms.). The total processing time has a standard deviation of $7.9250*10^5$ms (13.2min). The difference between average and median and the descriptive statistics indicate a right-skewed distribution (80.322). Descriptive statistics measured to be robust by comparing to 10 other random subsamples of the overall dataset. The right-skewed distribution indicates a Weibull distribution that approximates the distribution of residence time best compared to other hazard models (cf. Fig. 3).

### 4.2 Empirical Results

The previous section illustrated that the distribution of trade bookings shows declining residence time and that times are positive and not normal-distributed. That is why we regress all 1,000,155 order lifecycles as a cross-sectional dataset and investigate the influences using a Weibull-distributed hazard function model. Results of the regression analysis explain the influence of each individual entity within the four factor categories to the residence time (cf. Table 1.).

The model variables for slicing and modifications show high significance as the *p*-values are below the 1% significance level. Partial executions (that are a proxy variable on how granular an order shall be sliced relative to the average order size) increase the likelihood for an order to reside longer in the order book by 16.99% compared to the average limit order. Modifications to orders increase the likelihood of not being executed by 75.54%. This gives a first indication that order should be sliced into equally small orders near the average order size and that modifications should be avoided or substituted to early deletions and resubmissions.

All specification variables show high significant influence. For each percent that order limits are set more aggressive (e.g., near to the midpoint) the likelihood of execution increases by 9.28%. The coefficients for order sizes are rather low in comparison to the average number of shares per order (original order volume: 849.0 and hidden order volume: 492.23). Stronger influence is given by the order type. Compared to limit orders, an *IcebergOrder* has 257% higher likelihood to reside in the order book. Factors that are often discussed in the context of so-called “high-frequency trading” show negative influence on order lifetimes. Orders that are submitted by algorithms in the Automated Trading Program of Deutsche Boerse AG (*isATP*) have a 214% higher chance for a shorter lifecycle. Orders that are submitted based on co-location to the Xetra system (within the same data center) have an 18.6% higher change to reside shorter in the order book. The coefficient of the *isBuy* variable indicates the buy-pressure effect, which increases of the DAX 30 index in the 10-day-observation period and filters so-called momentum effects from the overall model.

For the execution and restriction the significance of the results is ambiguous. *AuctionOnly* trade restrictions increase the likelihood of an order residing in the order book by 343.5%. *TriggeredStopOrders* are executed relatively slow as those have a 130.5% higher likelihood for longer lifetime times as the second limit of this order type blocks the execution in the order book. *DeletionByUsers* has an 83.1% higher likelihood to occur earlier than an avg. *Execution* (excluded from regression table due to perfect colinearity), while *DeletionBySystem* has no significant influence to length of the order lifecycle. The coefficients indicate that the overall model estimates both (*Execution* and *DeletionByUsers*) to have shorter lifecycles than *DeletionsBySystem* (Xetra). Deletions are double as likely as executions to end lifecycles.

Additionally to the order specific effects, the model is controlled for time- and instrument-specific influences. All time-specific influences show a high significant influence on the lifetime of orders. The likelihood of orders residing in the order book increases throughout the trading day. The order survival likelihood increases until 2pm. (before *Hour14*) and is then up to 61.36% higher in comparison to the opening hour at 9am. When the US markets open after 3pm. (at *Hour15*) the likelihood of longer lifecycles diminishes to 9.9% compared to 9pm. In the last two trading hours the likelihood of orders residing shorter in the order book reduces by 0.62% (4pm) and 5.9% (5pm) compared to the opening hour in the morning. The dummy variables for the 10 days show influence to the model. While the second day has the highest likelihood of longer order lifecycles, the fifth day is highest likely to have the shortest lifecycle. As this is not observable for the second week, no evidence for weekly patterns is given.

**Table 1.** Regression results for order lifetimes in the Xetra system

| | Coefficient | Std. Error | z | *p*-Value | |
|---|---|---|---|---|---|
| const | 8.5598 | 0.017309 | 494.53 | <0.00001 | *** |
| PartCount | 0.16992 | 0.007888 | 21.54 | <0.00001 | *** |
| ModCount | 0.75539 | 0.019836 | 38.08 | <0.00001 | *** |
| Aggressiveness | -0.09275 | 0.000995 | -93.22 | <0.00001 | *** |
| OriginalOrderSize | 0.00013 | 0.000002 | 72.05 | <0.00001 | *** |
| HiddenOriginalSize | -0.00000 | 0.000000 | -32.68 | <0.00001 | *** |
| IcebergOrder | 2.57515 | 0.034988 | 73.60 | <0.00001 | *** |
| IsColocated | -0.18630 | 0.005845 | -31.87 | <0.00001 | *** |
| IsATP | -2.13995 | 0.008471 | -252.61 | <0.00001 | *** |
| IsBuy | -0.02796 | 0.004740 | -5.90 | <0.00001 | *** |
| DeletionByUser | -0.83128 | 0.010503 | -79.15 | <0.00001 | *** |
| DeletionBySystem | 0.76843 | 1.255930 | 0.61 | 0.54064 | |
| MainTradingOnly | 1.76820 | 0.028052 | 63.03 | <0.00001 | *** |
| AuctionOnly | 3.43514 | 2.368360 | 1.45 | 0.14694 | |
| ImmediateOrCancel | -8.43671 | 0.418768 | -20.15 | <0.00001 | *** |
| TriggeredStopOrder | 1.30525 | 0.574475 | 2.27 | 0.02308 | ** |
| Day2 | 0.04617 | 0.011087 | 4.16 | 0.00003 | *** |
| Day3 | -0.02982 | 0.011122 | -2.68 | 0.00734 | *** |
| Day4 | -0.06094 | 0.010978 | -5.55 | <0.00001 | *** |
| Day5 | -0.34473 | 0.010443 | -33.01 | <0.00001 | *** |
| Day6 | -0.28395 | 0.010820 | -26.24 | <0.00001 | *** |
| Day7 | -0.26625 | 0.010770 | -24.72 | <0.00001 | *** |
| Day8 | -0.18601 | 0.010978 | -16.94 | <0.00001 | *** |
| Day9 | -0.19105 | 0.010808 | -17.68 | <0.00001 | *** |
| Day10 | -0.11171 | 0.011197 | -9.98 | <0.00001 | *** |
| Hour10 | 0.18133 | 0.009936 | 18.25 | <0.00001 | *** |
| Hour11 | 0.25199 | 0.010059 | 25.05 | <0.00001 | *** |
| Hour12 | 0.42427 | 0.010718 | 39.58 | <0.00001 | *** |
| Hour13 | 0.61362 | 0.010904 | 56.28 | <0.00001 | *** |
| Hour14 | 0.21488 | 0.009749 | 22.04 | <0.00001 | *** |

| | Coefficient | Std. Error | z | *p*-Value | |
|---|---|---|---|---|---|
| Hour15 | 0.09935 | 0.009247 | 10.74 | <0.00001 | *** |
| Hour16 | -0.00629 | 0.008791 | -0.72 | 0.47442 | |
| Hour17 | -0.05982 | 0.010804 | -5.54 | <0.00001 | *** |
| Bayer | 2.35043 | 0.013829 | 169.96 | <0.00001 | *** |
| Telekom | 2.79782 | 0.017063 | 163.97 | <0.00001 | *** |
| Lufthansa | 3.63753 | 0.022299 | 163.12 | <0.00001 | *** |
| Daimler | 2.10996 | 0.012932 | 163.16 | <0.00001 | *** |
| Linde | 2.01747 | 0.014593 | 138.25 | <0.00001 | *** |
| Metro | 3.30488 | 0.020768 | 159.13 | <0.00001 | *** |
| ThyssenKrupp | 2.78849 | 0.015916 | 175.20 | <0.00001 | *** |
| DeutscheBoerse | 2.79091 | 0.020544 | 135.85 | <0.00001 | *** |
| Beiersdorf | 3.56327 | 0.022476 | 158.54 | <0.00001 | *** |
| DeutschePost | 3.49690 | 0.020979 | 166.69 | <0.00001 | *** |
| MAN | 2.39623 | 0.016437 | 145.79 | <0.00001 | *** |
| RWE | 2.53589 | 0.013596 | 186.52 | <0.00001 | *** |
| Merck | 2.67144 | 0.017077 | 156.44 | <0.00001 | *** |
| SAP | 2.26996 | 0.013376 | 169.70 | <0.00001 | *** |
| K+S | 3.06688 | 0.019242 | 159.39 | <0.00001 | *** |
| Henkel | 2.70532 | 0.017293 | 156.44 | <0.00001 | *** |
| FreseniusMedical | 2.41617 | 0.016005 | 150.96 | <0.00001 | *** |
| Allianz | 1.52285 | 0.012100 | 125.86 | <0.00001 | *** |
| E.ON | 2.87333 | 0.014617 | 196.57 | <0.00001 | *** |
| BMW | 2.2648 | 0.014973 | 151.26 | <0.00001 | *** |
| Salzgitter | 3.30918 | 0.023421 | 141.29 | <0.00001 | *** |
| BASF | 2.61589 | 0.014080 | 185.79 | <0.00001 | *** |
| DeutscheBank | 1.80625 | 0.012306 | 146.78 | <0.00001 | *** |
| MuenchnerRueck | 1.80674 | 0.013619 | 132.67 | <0.00001 | *** |
| Postbank | 3.93895 | 0.032650 | 120.64 | <0.00001 | *** |
| Siemens | 1.91155 | 0.011868 | 161.06 | <0.00001 | *** |
| Adidas | 2.93785 | 0.017509 | 167.80 | <0.00001 | *** |
| Commerzbank | 4.05485 | 0.029420 | 137.83 | <0.00001 | *** |
| Infineon | 4.20838 | 0.057171 | 73.61 | <0.00001 | *** |
| sigma | 2.36814 | 0.001678 | 1411.66 | <0.00001 | *** |
| Chi-square(61) | 297655.6 | | p-Value | <0.00001 | *** |

**/*** = significant at a 5%/1% level.

All instruments are flagged by a dummy variable for the ISIN of each stock. We selected VW to be the benchmark for all other instruments as VW orders have the shortest lifecycles in the sample. Results show a highly significant influence that all other instruments have 152-420% higher likelihood for longer order lifecycles. This gives evidence that VW has to be treated as a special case in 2009, which is reasonable due to the price peak of VW in 2008, where the price jumped intraday from 520-1005 Euro. A Chi-squared test indicates overall model validity.

# 5 Discussion

## 5.1 Implications on Research

The results of the empirical analysis are in line with previous related work in the field of electronic finance and market microstructure research. Additionally, this study contributes to this field by giving additional insight on how concrete order specifications influence the survival of open orders in the order book. Thereby, we analyze the a specific set of patterns and components for financial service system interaction between the broker and the market system as proposed more generalized by Böhmann et al. [1]. We give first empirical evidence how brokers and their trader should behave when handling orders for their customers. This study focuses based on Böhmann et al. on the critical service system interactions with market system and the brokers and traders and enable a theory-inspired design of service interactions[1]. Related work (that previously analyzed influencing factors such as aggressiveness) can also explain order survival times in our study. Results also show that various other factors mentioned in IS and finance literature are influencing the complex interaction with the market system too. From the perspective of a broker and its traders, we can give first empirical evidence, on how to slice (research question 1) and modify (research question 2) orders, when interacting with the market system. This can also help for design and decision support as it is shown in the next section on practical implications of the found results.

## 5.2 Practical Implications

In addition to the numerical results and the implication on research, the results of the study helps brokers to specify their order for better slicing and less modification. First of all, this study uses various groups of influencing factors to give evidence of how each factor influences the execution time of orders.

Each control variable in this model is also a filter for the effects that can explain this variable. Due to the large number of influencing factors each coefficient gives good indication on the raw influence of this specific factor. These coefficients were tested multiple times with other dataset samplings and show robustness for these alternative setups.

Next to the empirical results on the raw effect of each factor, the coefficients of the regression can be applied as a decision framework or rule of thumb on to the influences of specification, slicing and modification orders (research question 3). As the coefficients show how each factor influences the likelihood to be executed faster or slower than the average limit order, these coefficients can be used as a lookup table for the overall execution likelihood for a given order specification.

As an example assume that a broker has to trade 100.000 Siemens shares (average order size: 849.3 shares / average order lifetime: 40,452ms) within an hour, but the average order sizes and lifetimes lets us expect to be executed in 78min (factor 0.3 longer than 60 min) plus a stock-specific coefficient for Siemens of 1.91155 (times longer order survival). Then he might suggest to trade between 4pm and 5pm (coef.: -

0.00629) and to set the limit 1% more aggressive (coef.: -0.09275) than with an average order. He might decide to use algorithmic support/ATP (coef.: -2.13995) and neglect to modify his order to lower the suborder lifetimes. So, 78min * (1 + (1.91155 - 0.00629 - 0.09275 - 2.13995)) would result in an expected execution time of 52.46min and the broker would be able to slice his sub-orders to the average order size without the risk of additional waiting time for unfilled partial execution. If he would slice the sub-orders a bit larger than the average order size than the overall execution time raise to 52.46min * (1 + 0.16992) = 61.73min (due to partial executions) and he would break the time limit. If he recognizes that the order will not be executed as expected, the order should be deleted early instead of being modified open in the order book.

In general, modifications have a much worse effect for a trader than specifying sub-orders with wrong granularity and sizes. For each multiple that an order is bigger than the average order size the likelihood of not being executed increases by 16.99%. Compared with a modification this increases the likelihood not to be executed to 75.53%.

From a general point of view, traders should avoid sending one single big order to the order book. Each partial execution increases the likelihood of longer execution times (independent from the order sizes). In changing market situations traders should avoid waiting long with modifications and should use deletions early instead. Traders should avoid estimating execution times or slicing and modification decision just by the aggressiveness and the market situation. The results show that traders have lots of control opportunities just by giving a good order specification. These likelihoods work independently from overall market situation. Previous research shows that trader specifications like the aggressiveness have much higher influence to execution time than the general market situation. Aggressiveness also implies specific information like the own position in the order book independent for liquidity and spread. Future research might analyze these aspects that are unobservable with the structure of the given dataset and will be discussed in the next paragraph. Overall, our empirical analysis provides not only insight of the magnitude of the influencing factors that a trader can specify, but also the ability to support decisions on how to slice orders in good granularity and modify orders less.

### 5.3 Limitations

Although the high significance of the results, this investigation just focuses on financial market orders and within this field of research just to orders on German, high-liquid equities. As this might influence the generality of results, we assume that the analyzed dataset is a broad set of observations and that the covered effect should be transferable at least to other equities traded across Europe and other forms of securities trading. The dataset covers just 2 weeks with a less volatile trading period. Even as all control variables show plausible results, there is the risk that the selected time range might decrease generality. Due to computationally complexity of the regression model the dataset had to be subsampled to a set of 1 mil. random selected order lifecycles. Despite that random selection might induce a slight additional bias. The subsampling was repeated ten times to control the presented results and coefficients and significance levels stayed consistent. Due to a broken and missorted index column in the original dataset, it was not possible to reconstruct the order book of every observation. As market orders are not logged as lifecycles by the dataset, this order type was assumed to have a lifetime of less than a millisecond and excluded from the investigation. Multiple control and validation methods have been applied to check the robustness of the results and to avoid a bias resulting from dataset characteristics.

## 6 Conclusion

We analyzed our three research questions on how 1) specification and 2) modification of electronic orders influence the execution likelihood and on how 3) these orders can be managed, sliced and adjusted for a likely execution, by pre-analysing previous work in the field of IS and finance. We derived a hypothesis-based model by aggregating known influencing factors and analyzed the influence to order survival by applying a survival analysis to a unique message-based dataset on order lifetimes in the market system of Deutsche Boerse AG. We find new insights on how order slicing, partial executions and modifications influence the likelihood for a broker to fulfill his clients order in a desired time frame. We control for other influences known from related work and find similar relations and strength for these factors. Using the empirical estimated coefficents for each factor, we discuss the implications in general and give concrete advice for broker and trader on how to apply these coefficents as a applicable framework, when managing, slicing and adjusting orders for clients.

Certain potential limitations open up possibilities for further research. On the one hand, the data scope might be extended to a broader set of equities. On the other hand, there is potential to have a deeper look into the general market situation, other aspects of best execution that a trader can just observe, but not influence, like market liquidity, trading volumes or volatility that are unobservable with the dataset at hand. In general, this study supports the intermediary services of brokers and traders on how to specify slice and modify client orders so they can be fulfilled in a defined time frame.

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