Trading Heuristics in Financial Markets:
Technical Analysis and Round Number Effects

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Karlsruhe, October 2016 Felix Fritz

Contents

Chapter 1

Introduction

1.1 Motivation

Trading in financial markets is easy. Today, any person with an internet connection and a proper brokerage account can trade almost any financial security on all important exchanges around the world. However, making the *right* trades is extremely complicated and many empirical studies[1] suggest that both private and institutional investors often fail to do so.

Especially stocks seem to be promising investment instruments in order to obtain acceptable long-term returns. The negative trend in key interest rates during the last decade has hit the zero line implying a virtual absence of effective low-risk saving instruments. This is particularly worrisome with respect to the politically intended proliferation of private retirement provisions in Germany and other countries alike. In the view of the German government "private retirement provision is indispensable to maintain future living standards" (Federal Ministry of the Interior, 2011, p. 143). Considering the media coverage, we find an insistent narrative, which appears to be common knowledge, saying that "stocks are without alternative"[2] for wealth creation. Given that private persons have a necessity to invest in risky assets, e. g., stocks, the question of how to invest correctly imposes a great challenge to investors.

There has always been an intense discourse on how to increase wealth by investing in stock markets. What should we buy or sell and when should we do it? What risk should we take? How to diversify between stocks and other assets? Should we invest in single stocks or use baskets such as funds? Should we trade actively or be just long-term buy-and-hold investors? Undoubtedly, the list of questions is long and for each question, there are different answers depending on whom we ask and who is asking.

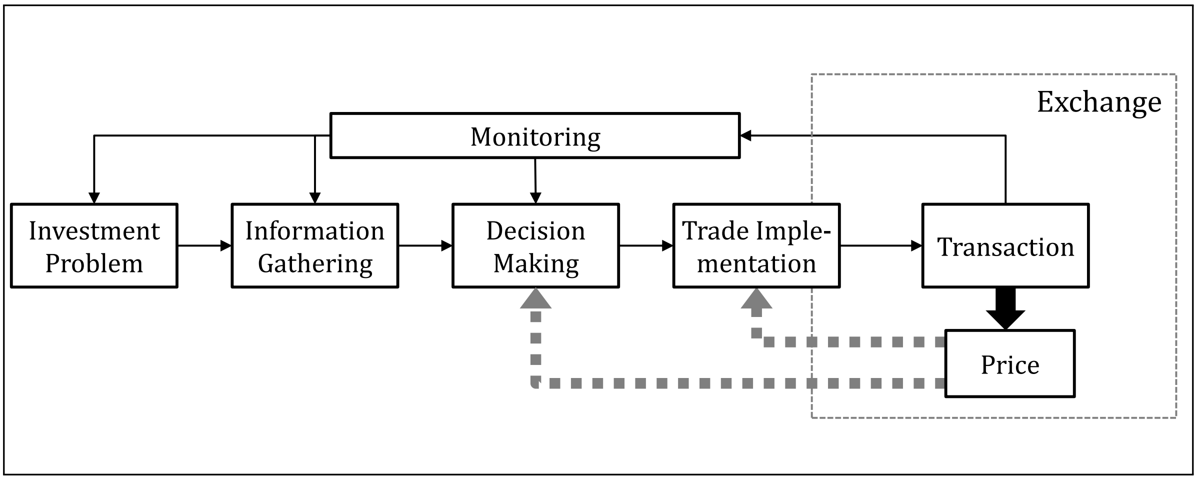

FIGURE 1.1: **Stylized Investment Process.**

Figure 1 illustrates a stylized investment process in order to discuss typical actions an investor would take. For simplicity, assume the investment problem[3] is to solely invest in stocks, which could be a sub-task of the overall investment problem. The investor needs to gather information on the instruments and on the methods to evaluate these instruments, in order to solve her investment problem. Based on this information, the investor needs to make decisions of what, when, and where to buy. Ultimately, she

[1]For example, Odean (1998b) and Barber and Odean (2000) analyze performance of private investor and find considerable underperformance. Busse et al. (2012) analyze a broad set of institutional investors; Wermers (2000) shows a (net) underperformance of fund managers which to a large extent is due to transaction costs and other expenses. Naturally, average results imply that a large group of the sample population performs much worse than the average value.

[2]This statement has been made by many industry experts, e. g., Andreas Utemann, Chief Investment Officer Allianz Global Investors (Die Welt, 2015) and Christoph Bruns, Managing Partner of the fund management firm LOYS AG (Handelsblatt, 2012)

[3]The investment problems of private persons (households) are considered in the household finance literature. Campbell (2006) provides an overview on this research area and discusses challenges of normative and positive household finance. Naturally, the "investment problem" of an investor has more dimensions than just investing free capital, such as expected income and consumption as well as associated risks, risk-free rate, utility preferences. Note that the discussion of these key points as well as an extended view on household finance is beyond the scope of this thesis.

implements her decision, for instance, by submitting an order to buy (or sell) some stock on the selected exchange. However, the investment process is not a static single-period problem but a continuous one, where inputs are constantly changing and decisions must constantly be monitored. It is evident that each step of this process cannot be solved optimally but is constrained by resources (e. g., information) and cognitive abilities (e. g., knowledge or information processing capabilities). Thus, investors will always try to use some simplification, that is, they use heuristics to solve their investment problem.

In this thesis, I use the term investment heuristic for any approach which addresses some problem the investor might be confronted with when managing the investment process. In this sense, classical academic models, such as Markowitz' Portfolio Theory (Markowitz, 1952) or dividend discount models (e. g., Gordon, 1959), can be considered as a type of investment heuristic when used to make investment decisions, since the models are based on a set of assumptions which simplify the complexity of financial markets. While academics typically propagate fundamental and statistical analysis -— at its core modern portfolio theory, the efficient market hypothesis, and the capital asset pricing model -— practitioners often rely on methodologies, which are less backed by academic theory and quantitative validation but by personal experience of experts and media narratives (Flanegin and Rudd, 2005). There exists a wide range of investment methods and heuristics which are summarized under the term Technical Analysis. Technical Analysis typically involves the recognition of price trends and trend reversals by means of visual recognition or pseudo-statistical calculations. Its origins date back to the Dow Theory propagated by Charles Dow in the 1920s. Hence, Technical Analysis is substantially older than modern finance theories but it seems to have survived until today.

However, the outcome of the investment process is not only affected by the choice of the used investment heuristics. Behavioral finance literature has shown that the investment outcome of human investors is affected by their cognitive limitations and biases caused by judgmental heuristics (mental shortcuts for making decisions). These cognitive heuristics and the resulting biases can influence the choice and the implementation of investment heuristics. First, behavioral biases can influence the choice of investment heuristic. For instance, in the context of judging probability, the availability heuristic means the overestimation of probabilities of events based on observed frequencies. This cognitive heuristic could bias the investor's choice to use some investment heuristics because it occasionally worked in the past, but the investor overestimates the probabilities that it works in general. Second, the implementation of the applied investment heuristics could be biased or superimposed by behavioral characteristics of the investor. For example, investors who have a home bias, i. e., the tendency to focus on stocks of companies located in geographical proximity, limit their trading heuristic to a subsample of local stocks they are familiar with.

Furthermore, cognitive limitations of human investors can lead to imprecise (quantitative) processing of information. An example often observed in practice is the reliance on specific key figures, such as round numbers or all-time highs and lows in the price history which receive a lot of media attention. Such reference points often influence the decision of investors, for instance, when they submit a limit order with a specific limit price biased towards some level.

On the other hand, cognitive limitations could to some extent be diminished by the investment heuristic. Given the investor sticks to a certain systematic strategy, she might be able to overcome her loss aversion as a result of the systematic investment approach. Interestingly, proponents of fundamental and technical investment heuristics often interpret results of behavioral finance differently. From the fundamental analysis point of view, behavioral effects mean a deviation from the norm (e. g., full rationality), while technical analysts see behavioral concepts as a basic principle of markets which justifies its use as a method to identify the induced deviation (Kirkpatrick II and Dahlquist, 2012, ch.4).

Whether biased or rational market participants, Technicians or Fundamentalists, the basic principle of markets is to reveal the market price of the traded asset by means of the interaction of all market participants and the information they trade on. In this sense, the market also reveals whether an investment heuristic used to trade contains information that contributes to the informativeness of the current price. Nevertheless, any trade – whether informative or not – will ultimately affect supply and demand for the stock that can be observed in the market. Fisher Black motivated the term *noise trading* for such trades, i. e., trading "on noise as if it were information" (Black, 1986, p.529). If we assume that behavioral biases and (ineffective) investment heuristics contain no information, they trade on noise and add noise to the market at the same time.

In this way, the market is affected by behavioral biases as well as investment heuristics. The more dominant a bias or heuristic is, the larger the potential effects should become. This means, there could be an observable link between trading that happens on the exchange and investment heuristics that are applied by some market participants. Empirically, we usually do not know what the intention behind a trade or an order was, but we can observe the outcome, i. e., price and volume. Hence, price and volume could provide insights on whether heuristics are used and how they, in turn, affect the outcome of the market. If so, the question arises whether the outcome and, in general, the functionality of the market is influenced negatively or positively. If we assume that informed traders (e. g., arbitrageurs) will profit from deviations from efficient price levels, the effect from noise trading should vanish quickly. Thus, only a very precise view on trading will reveal such effects, i. e., from a (market) microstructure perspective.

In his review of behavioral finance, Subrahmanyam (2007, p.24) states that "there [...] is room to analyse the fast-growing field of market microstructure and behavioural finance" and asks "whose biases affect prices". This thesis tackles these issues and provides insights into the link between investment heuristics and dimensions of market quality (e. g., trading activity, liquidity, and price discovery) by the example of Technical Analysis trading strategies and round number biases. Thereby I empirically show how imperfect[4] trading intentions influence the microstructure of trading.

[4]At this point, the term rational can be used as well, since the considered behavioral biases and investment heuristics are limitations to the ability to find optimal solutions. However, to be *rational* needs some definition of rationality, e. g., by some model or theory, while imperfect shall denote that an optimal solution of the investment problem is very hard or even impossible to find and, hence, some heuristics are applied. On the other hand, using heuristics can be rational in certain circumstances, for instance, when information processing costs are high. Both cognitive and investment heuristics basically fit in the concept of *bounded rationality*, which establishes an overarching theory. Simon (1955) postulates simplifications that people use to make rational choices, e. g., by simplifying the pay-off function of the outcome of some choice. An overview of related concepts and definitions is provided by Camerer (1998), among others.

1.2 Research Outline

This thesis aims to analyze the link between dimensions of market quality and investment heuristics as well as round number biases. These links are considered on the basis of empirical analyses of Technical Analysis and limit order clustering as well as buy-sell imbalances around round numbers. I consider these research objects because both are long known to matter for stock trading but still persist today. This motivates the debate on why such investment heuristics and biases persist and what consequence the high popularity in financial media (among other things) has. In both cases, it seems that market participants did not adjust their behavior over several decades[5]. To study potential effects, I pursue an empirical approach which is based on the processing of large and precise data sets, i. e., data spanning over multiple instruments and over a long sample period, yet, having a high observation granularity (e. g., tick data and order flow data).

In particular, Technical Analysis, which summarizes a large variety of price and volume based methods and indicators, is heavily promoted in recent years by the financial service industry and financial media. Both use it to provide 'profound investment tools' for their clients and users. Whether they believe such features are actually helpful for the investors' trading efforts or whether marketing plays a dominant role is hard to verify, but the latter seems likely considering the advertisements of software providers for Technical Analysis tools. These catchy tools and visualizations could result in increasing click rates and time spent on a financial website or increase the number of client trades for a broker, in particular, because Technical Analysis methods provide explicit trading recommendations in most cases. Thus, it seems possible that Technical Analysis plays a role for retail investors when making investment decisions, which is addressed by the first main research question.

Research Question 1. *Do investment heuristics that are summarized as Technical Analysis influence retail investor trading in speculative structured products?*

[5]In the case of Technical Analysis, the survey evidence of Lease et al. (1974) and Hoffmann and Shefrin (2014) on the usage of Technical Analysis by retail investors show similar results, although 40 years separate the studies

To shed light on this question, I analyze order flow data in speculative structured products traded on the Stuttgart Stock Exchange. These products are almost exclusively traded by retail investors and provide a promising basis to explore the behavior of retail investors (e. g., Meyer et al., 2014). In order to analyze Technical Analysis, i. e., trading signals to buy or sell, I implement recognition algorithms to determine trading signals from popular chart patterns and Moving Average strategies. The algorithm is an adopted version of the algorithm proposed by Lo et al. (2000). The Technical Analysis signals are then related to various dimensions of retail investor trading such as trading activity, returns, and holding duration.

In fact, retail investor trading increases around Technical Analysis trading signals. Furthermore, several recent studies support the view that investment heuristics related to Technical Analysis (still) play a role for institutional investors, too (e. g., Menkhoff, 2010). Hence, the question arises if trading on the larger and economically more important German stock market is influenced by Technical Analysis in a comparable manner as retail investor trading in structured products. Thus, I consider trading on Germany's largest stock market Xetra in order to assess the following question.

Research Question 2. *What is the relation between Technical Analysis trading signals and the market quality on Xetra?*

O'Hara and Ye (2011, p.463) characterize market quality as "a market's ability to meet its dual goals of liquidity and price discovery." Both aspects are typically measured along several dimensions by means of different proxies (Zhang et al., 2011). The electronic evolution of both trading systems and IT infrastructure of market participants have made stock trading much faster and increasingly automated (e. g., Jain, 2005; Hendershott et al., 2011). This has substantially supported the increase in liquidity and market efficiency over the past decades. The ability to process and react on information very quickly makes it necessary to analyze potential market quality effects in relation to Technical Analysis based trading in an immediate way. Thus, the measurement must be based on short intervals instead of being calculated as long-term averages. Existing studies consider Technical Analysis mostly on a daily basis or over short time periods. I fill this gap by adapting the recognition procedure for intraday data and use the procedure to analyze immediate effects on various dimensions of market quality. In particular, this includes an analysis of price discovery by means of a price decomposition derived from a state space model representation.

The second part of this thesis examines round number effects, which can influence the trading decisions and, especially, the trade implementation (see Section 1.1). Psychologically, human round number biases stem from limited cognitive abilities to handle large or precise numbers as well as a lot of numbers simultaneously (Schindler and Kirby, 1997). Furthermore, people often rely on reference points (anchors), such as round numbers like integers or multiples of ten, in order to make decisions (Rosch, 1975).

In the context of financial markets, where buyers and sellers meet to find a suiting price, round numbers can simplify negotiations as they limit the set of possible outcomes by serving as reference points (Harris, 1991; Kahneman, 1992). This was particularly relevant in times when much trading happened bilateral and often non-verbal on the trading floor. Today, stock exchanges are highly automated and fully electronic. Therefore, it seems unlikely that the negotiation problem still applies. However, there is international evidence that limit order clustering still is an empirical characteristic of limit order book trading (e. g., Bhattacharya et al., 2012), but the origins of the effect and its implications remain unclear in the context of fully electronic markets and trading systems. Thus, the purpose of the following research question is to confirm the evidence on round number effects for the German stock market and to obtain further insights regarding potential determinants of these effects.

Research Question 3. *How do round number biases influence trading on the German stock market?*

Since the analysis of stock trading on Xetra is based on public data and Xetra is used by many different types of traders, stock trading data from Stuttgart Stock Exchanges enables a deeper understanding of retail investor behavior with respect to round number effects. The additional information contained in order flow data allows for a deeper understanding on how round number effects convey into the market.

1.3 Structure of the Thesis

The remainder of this thesis is organized as follows. Chapter 2 provides basic information on the institutional setting of German security markets with a focus on retail investor trading. The chapter also describes the data sets obtained from these institutions, which will be used throughout the thesis. Furthermore, I give an overview of academic literature on the behavior and biases of investors when making financial decisions as well as on empirical findings on (retail) investor trading and performance. The last section of the Chapter 2 provides basic knowledge regarding empirical market microstructure with a focus on the measurement of market quality.

The two subsequent chapters present the main results of this thesis. Chapter 3 analyzes the role of Technical Analysis for retail investor trading in structured products on Stuttgart Stock Exchange and for the trading of blue-chip stocks on Xetra[6] Therefore, an algorithmic recognition methodology is introduced to reconstruct Technical Analysis trading signals. Chapter 4 examines round number effects in the German stock market[7]. The chapter proceeds by analyzing the presence and determinants of round number effects on Xetra. These results are complemented by a second analysis of stock trading on Stuttgart Stock Exchange in order to obtain evidence on retail investor behavior, which shall improve the understanding of the results from Xetra. Chapter 5 summarizes the results and discusses their implications as well as potential future research topics.

[6]The results on Research Question 1 presented in Chapter 3 is based on the paper Fritz and Weinhardt (2015), which has been presented at the 14th INFINITI Conference on International Finance (Dublin, Irleand) and which was invited to for presentation at the 33rd International AFFI Conference 2016 (Liege, Belgium). Research Question 2 is based on the work Fritz and Weinhardt (2016). The results have been presented at the 2016 Portsmouth-Fordham Conference on Banking & Finance (Portsmouth, UK) and the paper is invited for presentation at the 14th International Paris Finance Meeting 2016 and the 4th Paris Financial Management Conference 2016.

[7]Chapter 4 is based on the paper Fritz (2014), which has been presented at the 5th Financial Markets and Corporate Governance 2014 (Brisbane, Australia) and was invited for presentation at the 12th INFINITI Conference on International Finance (Prato, Italy).

Chapter 2

Foundations

This chapter provides basic information on the research objects of this thesis. I focus on German security markets with a special dedication to retail investor trading and behavior. First, the financial institutions and products considered in this thesis are introduced as well as the employed data sets provided by these institutions. Second, I discuss academic findings on investor behavior and biases in financial decision making as well as empirical findings on retail investor trading in practice. Third, basic knowledge on market microstructure theory with a focus on the measuring of market quality is provided.

2.1 Institutions

The empirical analyses conducted to answer the research questions postulated in Section 1.2 focus on financial markets in Germany. This section describes the German exchange landscape with a focus on stock trading and trading of structured products. The universe of structure product types is immense, hence, I will consider two popular and fairly standard types of speculative structured products namely plain vanilla warrants (henceforth warrants) and knock-out warrants, which are described in detail within Section 2.1.3.

With respect to the trading process discussed in Chapter 1, the investor's brokerage naturally plays an important role. Numerous brokers offer their services to retail investors. Most classical banking accounts come with the possibility to add a brokerage account. Furthermore, there are many online (discount) brokers offering accounts which are accessible exclusively online and come at relatively low cost. Typically these brokers have mobile application such that trading is possible from anywhere at any time provinding retail investors much more flexibility compared to the pre-internet era. Since financial markets have become fully electronic, brokers can offer their (retail) clients access to almost any exchange and any product. The high degree of automation promoted the rise of the derivatives industry as it has become very simple to issue new products and markets, e. g., contracts for difference (CFDs), binary options, and (other) structured products.

Due to the lack of broker data, I omit to describe the brokerage industry in more detail. The presented research on retail investors, in particular Section 3.5 and Section 4.6, takes a market-wide perspective, i. e., the retail investors participating in a market are considered as a group and, thus, the results provide evidence on the population of (retail) investors rather than on the individuals.

2.1.1 Deutsche Börse and Xetra

Deutsche Börse is the largest exchange operator in Germany and is the fourth largest equity exchange world-wide (as of May 2016). Deutsche Börse operates several market platforms and the largest German provider of post-trade services (Clearstream). Their fully electronic trading platform Xetra (current release Xetra 16.0) is the primary market for most major German stocks. With an overall order book turnover at the cash market of about EUR 1.058 trillion[1] in 2013 Xetra constitutes one of the largest stock exchanges world-wide.

Stock trading on Xetra has a dynamic flexible market model which includes continuous double auctions (limit order book trading) as well as call auctions. The normal trading schedule stipulates auctions at the beginning and at the end of the trading session as well as a midday auction. The full Xetra trading schedule is shown in Appendix A.1. Trading hours at Xetra are from 09:00 a.m. to 5:30 p.m. (CET). After trading

[1] According to the GDP report of the Statistische Bundesamt, trading turnover on Xetra is equivalent to about 38% the German gross domestic product in 2013 (EUR 2.821 trillion).

interruptions (e. g., volatility breaks) trading is typically initiated by a call auction to concentrate liquidity.

The Xetra system is designed to enable fast and large-scale trading. Deutsche Börse offers different connection bandwidths and co-locations to meet the demand of market participants for low-latency access. Over the last decade the share of high-frequency trading has increased considerably which also bolstered trading activity and liquidity. For example, in 2007 the reduction of latency with the Xetra 8.0 upgrade led to a significant increase of liquidity and a reduction of spreads (Riordan and Storkenmaier, 2012). According to a press release in August 2008 (Deutsche Börse AG, 2008), the share of algorithmic trading in overall order volume on the Xetra system is in the magnitude of 40 percent. Although exact numbers are not publicly available, it is likely that the amount is considerably larger in highly liquid stocks (cf. Gsell and Gomber, 2009) and has further risen in recent years.

Furthermore, Xetra allows for so-called designated sponsors who are required to "offer binding bid- and ask prices" (Deutsche Börse AG, 2012, p.1) based on specific requirements but receive a rebate on trading fees. Besides classical order types such as market, limit, and stop orders, continuous stock trading on Xetra allows for several non-standard order types. The official Xetra documentation (Deutsche Börse AG, 2015b) gives an overview on trading rules and all available order types in continuous stock trading on Xetra. Note that the referenced document is valid as of November 2015 and several changes have been made during the sample period analyzed in this thesis (2008 to 2013). However, the respective documentations are not publicly available anymore and therefore are not referenced here.

For expediency reasons, I only discuss those exotic order types which might be relevant for the analysis of the microstructure of trading. Hidden orders and iceberg orders are limit orders which are not or only partially (iceberg) displayed in the limit order book but have no time priority against visible order types, i. e., the hidden part of the order is executed only if it improves the current bid or ask price. With respect to market quality measures, hidden orders have an effect in the sense that trade executions can occur inside the bid-ask spread.

Midpoint orders are special orders which are aggregated separately from the limit order book and are executed at the midpoint of the bid-ask spread. However, midpoint orders only account for a negligible number of transactions. Based on the data sample from the Thomson Reuters Tick History introduced in Section 2.2, less than 0.01% of DAX30 transaction during continuous trading in December 2013 were due to midpoint orders.

In 2002 Deutsche Börse introduced the Xetra BEST functionality which offers an integrated feature for the execution of bilateral trades between the so-called Best Executor and an order flow provider based on reference prices from continuous limit order book trading on Xetra (Deutsche Börse AG, 2015a). Technically, a Xetra BEST order is executed against the Best Executor at a price better than current quotes or executed against the orders in limit order book, i. e., the order is automatically entered into the Xetra order book. The price improving characteristics of BEST orders lead to the observation of inside spread executions which usually have a price improvement of EUR 0.001 compared to the current bid or ask. Since this order type is a normal function of continuous stock trading on Xetra, excluding those trades seems inconvenient with respect to measures of trading activity, liquidity, and price discovery. In December 2013 the order type accounted for 0.64% of executed transaction in DAX30 stocks which seems to be sufficiently small to reject potential systematic effects on any result.

A detailed introduction and description of the employed data sets from Xetra follows in in Section 2.2.1.

2.1.2 Stuttgart Stock Exchange

Besides the fully electronic trading system Xetra, there are seven regional floor-based exchanges in Germany. Among these, Stuttgart Stock Exchange, which is operated by the Boerse Stuttgart GmbH[2], is the largest in terms of trading turnover but plays a minor role in stock trading, which is dominated by Xetra[3]. The business focus of Boerse Stuttgart is to provide exchange services which primarily address the trading needs of retail investors.

[2]For further information on the corporate structure of institutions associated with Boerse Stuttgart see `https://www.boerse-stuttgart.de/en/company/exchange/` (accessed on July 18, 2016).

[3]In 2014, the overall turnover in equities on Stuttgart Stock Exchange was EUR 87.8 billion compared to EUR 1259.6 billion on exchanges of the Deutsche Boerse Group. Source: Federation of European Securities Exchanges (`http://www.fese.eu/`).

The major segment of Stuttgart Stock Exchange is listing and trading of structured products. Structured products (also known as bank-issued products, securitized derivatives, and certificates) are technically bearer bonds issued by an investment bank that typically have a non-trivial payoff function depending on one or multiple underlying instruments. The structured products trading segment at Stuttgart Stock Exchange was introduced in 1999 and has grown considerably since then. At the end of 2014, there were 1.121 million structured products listed on Stuttgart Stock Exchange making up for more than 95% of all listed instruments on the exchange (Baden-Württembergische Wertpapierbörse, 2015).

In contrast to Xetra, Stuttgart Stock Exchange has a hybrid trading model which combines electronic limit order book trading and floor-based market makers (so-called quality liquidity provider). Especially for trading of illiquid instruments such as most structured products, the market makers of the EUWAX AG, which is subsidiary of Boerse Stuttgart GmbH, are necessary to ensure that trades are executed quickly at reasonable prices. In many instruments traded at Stuttgart Stock Exchange, client orders are usually executed against a market maker who sets prices with respect to some reference market. For example, orders in DAX30 stocks which are smaller than a given trade size are executed at the Xetra midquote price during Xetra trading hours. This implies that stock trading at Stuttgart Stock Exchange has virtually no price discovery function.

Similarly, trading of structured products does usually not reveal the price of the instrument as it is the case for exchange-traded options on Eurex[4], for example. Since the price of structured products is a function of traded instruments and other inputs (risk-free rate, maturity, etc.), prices can be calculated based on reference prices of the inputs and some valuation function. In practice, price quotes are typically provided by the products' issuing bank.

2.1.3 Bank-Issued Structured Products

Structured products denote a large universe of bank-issued investment instruments primarily addressing trading needs of retail investors. From a legal perspective, structured

[4]Eurex exchange is a derivatives exchange operated by Deutsche Börse (`http://www.eurexchange.com`). With a total trading volume of 1.5 billion contracts in 2014, Eurex is among the largest derivatives exchanges world-wide.

products are bearer bonds issued by an investment bank which have a non-trivial payoff function, such as derivative components with respect to some underlying instrument. Stock exchanges like Stuttgart and Frankfurt Stock Exchange list these products to make them tradeable and employ market makers to increase liquidity. However, it is also possible to trade the product with the issuing investment bank directly via over-the-counter (OTC) transactions. In contrast to funds or exchange-traded derivatives, structured products include an additional default risk due to the legal classification as bonds.

Structured products give retail investors the possibility to invest in underlyings (e. g., commodities, interest rates) and derivative strategies (e. g., options) to which they usually have no or only limited access, for instance, due to specific capital or admission requirements (e. g., for derivative exchanges such as Eurex), inconvenient market characteristics (e. g., commodity spot markets), or missing (broker) access to international markets. The vast universe of structured products covers a large range of underlyings and payoff functions. Naturally the benefits of such products come at a cost for the retail investor. Besides trading fees and bid-ask spreads, structured products contain a (price) premium charged by the issuing bank. These premia are contained in the price quotes of issuers which gradually decrease over the product lifetime (so-called life cycle effect). Since short-selling of structured products is not permitted, it is not possible to arbitrage the overpricing of products.

The product classification introduced by the Deutsche Derivate Verband[5] divides structured products into investment products (with and without capital protection) and leverage products (with and without knock-out). Investment products are intended to provide improved long-term return characteristics for the investor. For example, discount certificates are covered calls (i. e., underlying long and call option short) on the underlying instrument and provide a discount on the current underlying price while limited potential gains. Thus, the structured product allows retail investors to pursue strategies to which they have no access otherwise. Similarly, there are a numerous products which allow for other derivative features. Deutscher Derivate Verband (2016) provides an overview on most common types of investment products.

[5]The Deutsche Derivate Verband is an association of 15 leading issuers of derivatives in Germany (`http://www.derivateverband.de`).

With respect to Research Question 1 and trading heuristics like Technical Analysis, leverage products are of particular interest. Due to their characteristics, leverage products could be favored by retail investors who pursue active and speculative trading strategies. Empirically, the holding period of leverage is much shorter and trade frequency is higher. As the name suggests, leverage products include a leveraged payoff function, i. e., price changes in the underlying lead to disproportionate price changes in the leverage product. Thus, leverage products are (in most cases) more risky than a direct investment in the respective underlying but enable the investor to speculate with less capital requirements in large (net) positions. Since there are long and short (call and put) products, leverage products (as well as some investment products) allow retail investors to assume short positions on underlyings such as stocks.

Similarly to investment products, there exists a wide range of leverage products. In the following two common types which are empirically analyzed in this thesis are introduced. Deutscher Derivate Verband (2016) gives an extensive overview on other types of leverage products.

Warrants

Warrants are securitized plain vanilla call or put options and exist for many underlying instruments, such as stocks, indices, and commodities. As it is generally common for options, the specification of a warrant comprises time to maturity, strike price, exercise type, and subscription ratio. The payoff function at maturity is depicted in Figure 2.1. Before maturity the value of the warrant contains an additional time value, i. e., the implicit value of the option to buy or sell at the time of maturity (in case of European options). The fair price of a warrant with respect to the underlying can be calculated on the basis of option pricing models such as the Black-Scholes model.

Knock-out Products

Knock-out products or knock-out warrants (henceforth knock-outs) are securitized barrier options. Specifically, knock-out calls and puts are down-and-out calls and up-and-out puts, respectively. While the payoff at maturity is basically equivalent to warrants, the knock-out characteristic requires that the underlying price never reaches the barrier during maturity. The knock-out expires worthless when the barrier is touched

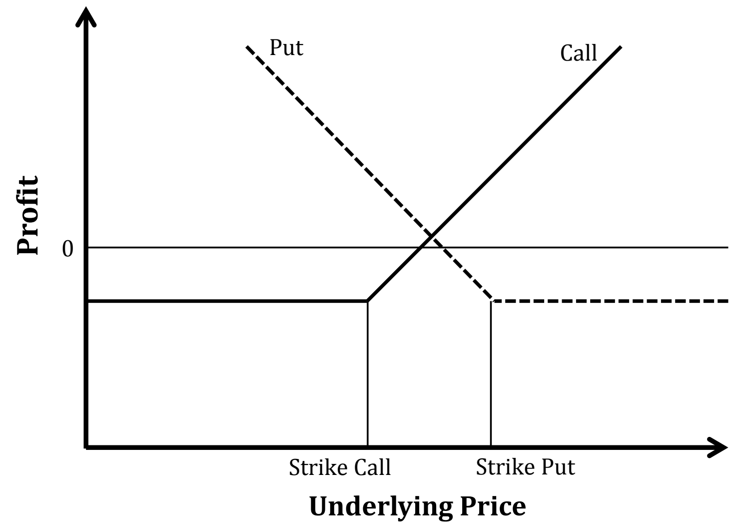

FIGURE 2.1: **Warrant payoff at Maturity.** This figure shows the payoff function of a call warrant and put warrant with respect to the price of the underlying at maturity. In both cases, losses are limited to the purchase price of the respective warrant.

or crossed from above (call) and below (put), respectively. Thus, knock-outs are basically riskier than standard warrants and are considered as highly speculative instruments for short-term trading.

For standard knock-out products barrier and strike price are equal. In case of open-end knock-outs, i. e., products without fixed time to maturity, there also exist knock-out calls (puts) with stop-loss for which the barrier is larger (smaller) than the strike. Furthermore, the barrier of open-end products is adjusted on a daily basis to compensate for the issuer financing cost, i. e., the issuer is not able to include the premium into the product price which then decreases until time to maturity, since maturity is unlimited. Due to the additional complexity of these products and the requirement of data regarding daily barrier adjustments, open-end products are not considered for the empirical analyses presented in Section 3.5.

Academic Literature on the Market for Structured Products

The academic literature on the market for structured products are basically along two directions. On the one hand, issuing and pricing of structured products (issuer perspective); on the other hand, behavior of retail investors trading structured products (investor perspective).

As mentioned above, structured products can be traded on exchange or OTC against the issuer. However, price discovery is generally quote-driven, i. e., issuers and market makers set prices. Since the product price also contains the product's premium, several studies investigate deviations between observed prices and theoretical fair values obtained by means of option pricing models. Wilkens et al. (2003) show price deviations in discount certificates and provide evidence for the life-cycle effect. Baule (2011) finds that issuers of discount certificates adjust overpricing with respect to the anticipated retail investor demand for the product. Fritz and Meyer (2012) analyze bonus certificates[6] and find that overpricing varies over the trading day, which reflects the varying risk associated with issuers' hedging strategies. Product premia in bonus certificates are estimated to impose costs of about 1% on the retail investors' initial position, on average. With respect to (open-end) leverage products, Entrop et al. (2009) find premiums ranging between five and ten percent of the certificate price, which theoretically implies profits for the issuers of 20% to 30% p.a.

Another branch of literature analyzes the trading behavior of retail investors in structured products. Schmitz and Weber (2012) analyze the behavior of discount broker clients in warrants and show that retail investor pursue negative feedback strategies (contrarian trading) and exhibit disposition effects[7], i. e., they are more likely to realize gains than losses. Meyer et al. (2014) find negative returns for retail investors trading leverage products which is driven by transaction costs and product premia. Further, they show that retail investors are attracted by news events. Similarly, Schroff et al. (2015) show that Google search volume in the underlying has a positive effect on trading activity in speculative leverage products while there is no effect in case of investment products.

Overall, the advantages of structured products, i. e., sophisticated payoff functions with derivative components, come at high costs for retail investors, who on average fail to earn excess returns on their trading activities. Hence, retail investor must either be

[6]Bonus certificates are investment products which protect the investor from adverse price movements below the bonus level up to the so-called security level. If the latter is breached, the bonus certificates remains a long position in the underlying.

[7]The disposition effect is discussed in Section 2.4

unable to realize that their trading efforts are ineffective, or they gain other utility from trading than profits. Several studies argue that retail investors who trade speculative structured products or, in general, derivatives have a strong preference for lottery-like payoff functions (Dorn and Sengmueller, 2009) while hedging seems to play no central role (Schmitz and Weber, 2012).

2.2 Data

This section gives an overview on the data sets and data sources used within this thesis. Furthermore, initial data processing steps, such as data cleanings and other adjustments, are described.

2.2.1 Thomson Reuters Tick History

Thomson Reuters Tick History (TRTH) is a large database of time-stamped market data for more than 45 million instruments[8]. I access TRTH via the services of Securities Industry Research Centre of Asia-Pacific (SIRCA[9]), which provides researchers access to several high-quality databases.

From TRTH I retrieve four types of data sets regarding stock trading on Xetra:

- End-of-Day data
- Intraday data
- Times & Sales data
- Depth data

End-of-Day data contains daily observation of opening, closing, highest, and lowest price as well as trade volume and corporate actions such as stock splits, dividend payments, and number of outstanding shares.

[8] See `http://thomsonreuters.com/en/products-services/financial/market-data.html` accessed on July 1, 2016.

[9] I thank SIRCA for providing access to their databases. For more information on SIRCA see `http://www.sirca.org.au`.

Intraday data refers to stock market data aggregated on intraday intervals of specific length such as 1-second, 1-minute, etc. For each interval, the same variables as for daily data are provided. In particular, open, high, low, and last (trade) price as well as volume are used for this thesis.

Times & Sales data provides a tick-based view on (stock) trading on Xetra. The data set contains all executed trades, quote revisions and call auctions time-stamped on a millisecond basis. For trade executions and auctions, price as well as executed volume are reported. Quote observations show best ask and bid price as well as the respective available limit order volume (number of shares). Appendix A.1 shows an example of Times & Sales data. Since I am primarily interested in continuous limit order book trading, executions of call auctions are disregarded as it is typically done in the literature. Note that the paritudar orders involved in some execution are not explicitly known. Thus, the trade direction, i. e., whether the liquidity demanding order was a buy or sell, must be estimated from the data. The procedure applied to infer the trade direction is described in Section 2.5.

Depth data contains information on the first ten levels of the bid and ask side of the Xetra limit order book time-stamped with millisecond precision. For each level price and limit order volume (number of shares) is reported. Each observation refers to an update of the limit order book such that the state of the limit order book can be reconstructed at any point of time.

I obtain these four datasets for all stocks of the Deutsche Aktienindex (DAX) and the Mid-Cap-DAX (MDAX) based on the index compositions on December 31, 2012. The sample of DAX (MDAX) stocks considered in this thesis range from January 1, 2008 (2009) to December 31, 2013. The last trading day of the year is disregarded due to the shortened trading session. Changes in the index composition are not considered to keep the set of stocks stable over time except ordinary shares of Volkswagen which are replaced by its preference shares. Any other stock which entered the DAX had been traded on Xetra before and analogously for stock which were removed from the index. In sum, there are thirty DAX stocks (DAX30) and fifty MDAX stocks (MDAX50) under consideration. The stock samples are listed in Appendix A.2 and A.3.

Besides stocks, Intraday data of the DAX index is obtained for the period January 2008 to December 2013. Furthermore, I use Intraday data on the volatility index

VDAX-NEW[10] (henceforth denoted as VDAX). The VDAX index is a proxy for market volatility and is calculated on the basis of implied volatilities of DAX options traded on Eurex[11].

Data quality

For empirical analyses, data quality is an important factor. With respect to TRTH tick-data (Times & Sales, Depth data), some potential data issues need to be considered. First, trade executions and quote updates, i. e., observations in the TRTH Times & Sales data set, are reported independently in the sense that time-stamps of trades and quotes can appear in the wrong order. Note that time stamps in the data sets are not provided by the exchange operator but are set by Thomson Reuters. Thus, biased time stamps could appear for trades and quotes if they are extracted by different processes in the trading system. For trades and quotes in the same millisecond, I compare trade price and size with the respective quote and quote change of the prevailing and subsequent quote observation and sort these observations accordingly. Misplaced trades and quotes having differing time stamps do exist but are very rare. Tests on the basis of more complex consistency algorithms show no relevant impact on trade- and quote-based measures such as spreads. In general, it is not expected that the described issue has a systematic effect on any variable calculated from this data set.

Second, it is suspected by researchers that data from TRTH is conflated, i. e., not all quote revisions are reported. In particular, changes which do not effect prices on some bid or ask level but only volume could be disregarded. While this might be critical for an analysis of high-frequency trading strategies, for instance on the basis of reconstructed orderflow from Times & Sales data, I do not expect any bias for the analyses presented in this thesis. Applied measures are typically aggregated on a lower frequency weighted by time and, thus, should not be systematically affected by missing short-lived quote updates.

Third, erroneous observations and missing data naturally can appear in the data recordings, for example due to system failures or incorrect data entries of Xetra or

[10] For details on the VDAX construction see `http://www.dax-indices.com/EN/MediaLibrary/Document/VDAX_L_2_4_e.pdf` accessed on July 3, 2016.

[11] The European Exchange (Eurex) is a Frankfurt based options and futures exchange owned by Deutsche Börse. `http://www.eurexchange.com`

Thomson Reuters systems. All observations are checked for inconsistent entries such as missing or zero values. If any data field is erroneous the observation is deleted. There are some instances when data reporting starts delayed, i. e., several minutes at the beginning of the trading day are missing. In most cases, this is uncritical to the analyses as the first and last minutes of each trading session are disregarded anyway. If there are longer gaps in the data the whole trading day is taken from the sample.

Data from the Thomson Reuters Tick History is a standard data source in financial market research and has been applied in many academic studies. Overall, I believe there is no impact from potential data issues on any results presented in this thesis.

2.2.2 Boerse Stuttgart Research Database

The Boerse Stuttgart Research Database[12] provides an in-depth view on trading at Stuttgart Stock Exchange and thereby enables researcher to analyze retail investor trading and structured products. I obtain two datasets from Boerse Stuttgart:

- Master data
- Order flow data

Master data describes the instruments traded on Stuttgart Stock Exchange. Since there exists a vast number of structured products and most have complex derivative features, information on the explicit product characteristics is indispensable for researching this trading segment. I use master data on knock-out products and warrants (without open-end products[13]) described in Section 2.1.3 ranging from January 1, 2009 to December 31, 2013. I only use instruments for which complete master data information is available. The sample contains 266,783 traded instruments, in total. Table 2.1 shows the relevant data fields of the *Master data* and an explicit example for a knock-out product. *Order flow data* contains all order submissions, modifications,

[12] I thank Boerse Stuttgart for providing data for this thesis. For further details on the Boerse Stuttgart Research Database see `https://www.retailinvestmentconference.org/data-for-research/data-for-research.html`.

[13] Open-end products have no fixed (limited) time-to-maturity. In case of option-like products such as knock-outs, the product's strike price is usually adjusted on a daily basis to compensate the issuer for the cost and premium of the product. Since the strike price updates are not part of the database, these instruments are not considered for the analysis presented in this thesis.

TABLE 2.1: **Boerse Stuttgart Research Database – Master Data Example.** This table shows a master data example entry of a warrant product traded on Stuttgart Stock Exchange. Only an extract of relevant data fields is printed. The shown product is a classical warrant product (German: "Optionsschein") on the DAX index by Commerzbank AG.

Data Field	Value
Type	WAR
Option Type	Call
ISIN	DE000CK7XFH4
Product Name	Optionsschein
Exercise Type	a
Underlying Instrument	DAX
ISIN Underlying	DE000CK7XFW3
Underlying Type	IND
Strike Price	7050
Expiration Date	05.04.2012
Subscription Ratio	0.01
First Trading Day	22.03.2012
Last Trading Day	04.04.2012

deletions, and executions at Stuttgart Stock Exchange. 2.2 shows all relevant data fields and an exemplary order execution. The main advantage of order flow data compared to Times & Sales data from TRTH is that it allows for a much more detailed view on investor behavior since all messages from investors to the exchange are known. In particular, the trade direction (buy or sell) of the executed order is known. In Chapter 3, I use order flow data for the above mentioned knock-out products and warrants, which comprises about 3.7 million executions. In Chapter 4, I analyze about 1.62 million trades in DAX30 stocks executed at Stuttgart Stock Exchange.

TABLE 2.2: **Boerse Stuttgart Research Database – Order Flow Data Example.** This table shows a trade execution (message code "011") recorded in the order flow data base. The traded instrument is the product shown in Table 2.1. Only an extract of relevant data fields is printed. The shown trade. Note that in practice reported trade execution do not contain order-level information such as limit price. In this example, this information is updated from the order history (submission, modification, etc.).

Data Field	Value
Message Code	011
Timestamp	2012-04-03 14:37:11.780
ISIN	DE000CK7XFW3
Buysell	K
Size	3081
Limit	0.3400
Stoplimit	-
Trade Price	0.3400
Trade Quantity	3081
Routing ID	xxxx

2.3 Behavioral Biases in Financial Decision Making

Standard financial market models assume that market participants act fully rational, i. e., they make decisions based on all relevant information in order to maximize their utility. However, through the observation of actual investor behavior the assumption of fully rational investors is not always consistent, as the literature discussed in the next section shows. In the research area behavioral finance, shortcomings of investors' decision making are analyzed with respect to the impact on the behavior of investors (among others, trading activity and portfolio choice) as well as on the market and, in particular, market prices. Thereby behavioral finance has helped to understand many financial market phenomena, which are considered as inefficiencies under classical assumptions, e. g., the equity premium puzzle[14].

[14]The equity premium puzzle (Mehra and Prescott, 1985) describes the empirically high average return of stocks (equity) compared to other asset classes that cannot be justified by the risk-return ratio of the stock. This means, investors demand a (unexpectedly) high risk premium to hold stocks. Behavioral factors, such as prospect theory preferences, discussed in Section 2.3 provide explanations for the puzzle, because it implies a substantial loss aversion of investors (Barberis and Huang, 2001) such that an additional risk premium is required to compensate for holding stocks.

This section provides a brief discussion of the behavioral finance literature focusing on aspects that are related to results presented in this thesis. For an extensive introduction and further discussion of behavioral finance topics, I refer to literature overviews by Thaler (2005) and Subrahmanyam (2007).

Barberis and Thaler (2003) cluster cognitive limitations in decision making into two components that affect the behavior of investors in a financial market context. First, how investors form beliefs about the current state and future outcomes. Second, what preference investors have with respect to the outcome of an investment. Both components can have a significant impact on asset prices (e. g., in case of the equity premium puzzle) and on the individual investment performance.

Besides the consideration of psychology findings on cognitive biases in decision making, behavioral finance is based on the concept of limited arbitrage. This concept disregards the assumption of rational agents who enforce efficient prices and ultimately push irrational and uninformed traders (noise traders) out of the market. I discuss the concepts of limited arbitrage and noise trading within Section 3.6.

As mentioned in Section 1.1, I differentiate between psychological heuristics for decision making, which cause behavioral biases (deviations from rational decisions), and investment heuristics, which intend to overcome optimization limitations occurring within the investment process. The latter establishes the framework of "bounded rationality" (Simon, 1955, among others), which considers the application of simplifications as rational behavior, since the full problem cannot be solved optimally. Naturally, psychological heuristics can influence the choice and implementation of an investment heuristic. For instance, cognitive limitations of humans make it impossible to process all information sources that might be relevant for an investment decision, thus, it is rational to focus on certain information. However, this focus could be biased by other behavioral factors or be influenced by the choice of investment heuristics. In case of Technical Analysis, the role of news about a stock company is considered to be only of subordinate importance, since it is assumed the market price will reflect the necessary information on the future price development anyway (cf. Section 3.3).

In general, the relation between biases is ambiguous and presumably varies between individuals. Related research[15] typically isolates single biases, for example, through a certain framing of an experiment task, in order to make assertion about the cognitive heuristics causing the bias. Considering the investment reality of (human) investors, behavioral effects are assumingly diffuse and superimpose each other. Hence, it is difficult to argue what bias plays a dominant role for the application of Technical Analysis and for round number effects based on a market-wide consideration. In the following, I briefly discuss cognitive limitations which are expected to affect the usage of Technical Analysis and round number biases. More specific implications with respect to the trading and investment outcome of retail investors are discussed within the next section.

Beliefs

The way people make beliefs is influenced by numerous cognitive heuristics which have evolved in the evolutionary process that formed human behavior. Some of them have implications for financial decision making as they can cause deviations from rational economic behavior. Some biases stem from or are related to the inability to handle randomness in a proper way. A reason might be that during the human evolution, the quick assessment of deterministic and causal links is a more important ability for survival, while probabilistic reasoning has fewer direct applications. Although literate persons like statisticians undoubtedly are able to understand and handle randomness, they still can be affected by related biases when they have to make decisions quickly or subconsciously.

In several works, Kahneman and Tveserky have established the concept of fast (System 1) and slow (System 2) thinking. While slow thinking tends to be more rational and is able to perform statistical and mathematical calculations, fast thinking, which is often associated with "gut decisions", is intuitive and allows to process more information subconsciously without requiring much mental effort. However, System 2 is more likely to be affected by biasing (cognitive) heuristics. In the following, I describe several beliefs that can consciously or unconsciously affect financial decision making and trading.

Overconfidence appears when people are to sure about the outcome of an uncertain

[15] Several of the initial works on biased decision making are collected in Kahneman et al. (1982), which resulted from a large research program supported by the Office of Naval Research in the U.S.

event. Overconfidence causes people to state confidence intervals regarding future outcomes that are to narrow. Furthermore, the chance of occurrence and the impact of improbable events is neglected. Overconfidence can have implications for portfolio choices and trading as people make decision based on imprecise estimates (information) of future states, which means they might trade on bad information potentially causing bad trading results.

Representativeness is a heuristic causing biased judgments of probabilities on the basis of similarity of a realization compared to population characteristics. For instance, this occurs when people assess the probability that an event is of a certain type by relying on the level of representativeness of the event for the type, but disregard potential other factors, such as prior probability, sample size, or frames. The tendency to infer (statistical) properties of the sample population on the basis of too few observations, which are assumed to be representative for the population, is referred to as the "law of small numbers" (Rabin, 2002).

In case of investment decisions, representativeness can be problematic when strategies are considered as profitable on the basis of a few positive events. Also the reliance on trends as a result of 'streaks' of subsequent positive returns might be related to this heuristic. Kahneman and Tversky (1972) find evidence on this phenomenon in their experiment in which participants judged sequences of coin tosses containing the same number of heads and tails less probable if they contain longer streaks (subsequences of the same type, e. g., three heads then three tails). Similarly, there is experimental evidence that in simulated random walks of (stock) prices are perceived to contain trends (i. e., streaks of the same type) based on only few observations and even if participants are told that observations are actually simulated random walks (De Bondt, 1993; Bloomfield and Hales, 2002).

The *availability* bias denotes the behavior when people estimate the likelihood of an event "by assessing the ease with which the relevant mental operation of retrieval, construction, or association can be carried out" (Tversky and Kahneman, 1973). In a financial decision making context, availability could affect investors' perception of risk and return prospects of assets on the basis of easily available information. Kliger and Kudryavtsev (2010) show that the stock price reaction to analyst recommendation revisions differs depending on the direction of recent market returns, which they interpret as a result of the availability bias. Availability is also related to recency, i. e., the tendency to rely on things that were perceived more recent. Obviously recency could bias decisions by overweighting more recent information compared to other relevant data. Similarly, investors could overestimate unlikely events that had a tremendous impact on themselves in the past, since it comes to mind more easily.

Anchoring makes people to form judgments of outcomes that are biased towards some initial value (anchor). This effect has been shown in experiments by providing participants random numbers that in fact biased their estimate, although the numbers were completely irrelevant for the estimation task (Kahneman et al., 1982, ch.1). In the context of financial decision making, anchors can appear in several ways. First, the communication and presentations of stock prices often takes place in the form of key figures, e. g., when the DAX index approaches or breaks a level of 10,000 points, although this value should theoretically be as likely or important than 10,123. This effect is also related to round numbers, such as integers, which often serve as anchors. Second, the buying price of a stock position can have a tremendous influence on the subsequent behavior of the investors (Odean, 1998a; Shapira and Venezia, 2001). Similarly, price targets recommended by analysts might serve as anchors for investors leading to estimates biased towards the target of the analyst.

Belief perseverance is the tendency of people to stick to their initial belief despite opposing evidence, or, even to misinterpret the evidence in a counterfactual way (Lord et al., 1979). A related effect is the confirmation bias that occurs when people specifically search for evidence which supports their initial hypothesis, while disregarding contrasting information. With respect to investment heuristics, such biases could motivate investors to search for trading signals that confirm a decision they already have made, e. g., to buy some stock because they like the company. Park et al. (2010) provide empirical evidence for a confirmation bias among investors processing information from finance message boards.

Preferences

Preferences describe how an investor orders different alternatives based on the utility she gains from each alternative. In finance, the formulation of preferences are used to describe how an investor values the outcome of an uncertain investment. Depending on her preference for risk, the investor probably will choose different assets or, more general, build a different portfolio of assets. The von Neumann-Morgenstern utility theorem (Von Neumann and Morgenstern, 1944) shows that if the utility functions of investors have certain characteristics, investors will take the choice that maximizes the expected value of their utility function. While the framework of expected utility provides the basis of the analysis of rational economic behavior, there is much empirical evidence that expected utility framework is often not the right approach to describe reality, as elaborated by Rabin (1998). Consequently, several other models and theories to describe preferences have emerged, of which Barberis and Thaler (2003, p.16) argue that "prospect theory may be the most promising for financial applications".

Prospect theory was introduced by Kahneman and Tversky (1979) and includes several features of human decision making, such as reference dependence, loss aversion, and non-linear probability weighting. The main characteristic of the proposed utility function is the assessment of the utility gained from some choice (gamble) by valuing the outcome (payoff) and the (perceived) likelihood of that outcome, receptively. The value function is increasing and concave for gains and is decreasing and convex for losses. Additionally, value decreases stronger for losses than it increases for gains, i. e., the decision maker is assumed to have a loss aversion. Since gains and losses are always considered with respect to the current wealth, a natural reference point is established to which prospects are evaluated. Moreover, prospect theory applies a probability weighting function that transforms actual probabilities such that small probabilities are overweighted. An interesting implication in the context of financial markets is that investors who have prospect theory preference will choose investments which are similar to lotteries, i. e., gambles that have a high probability of a small loss and a small probability of a high gain. In terms of (expected) returns of an investments, prospect theory implies a preference for right-skewed distributions.

The lottery characteristics of investments predicted by prospect theory preferences of investors could provide an explanation for the high level of speculative, lottery-like stock trading among retail investor, which is discussed in Section 2.4. However, playing a lottery could have a value for an investor, namely as a form of thrill and entertainment. In this sense, the investors becomes an utilitarian trader, who pays for his demand for entertainment by below average returns as she loses against informed traders and due to trading costs. Whether in the context of financial markets the demand for gambling and entertainment makes prospect theory preference a suiting utility model assumption, or whether demand for gambling is a result of the intrinsic preference of people being as described by prospect theory is difficult to verify, however.

Another practically motivated aspect regarding utility preferences and the outcome of uncertain payoffs is the assessment of the uncertainty involved in the utility evaluation. That is, if the investor does not exactly know what the prospects of the uncertain payoffs are and she is not completely sure about her own preferences, there is a second layer of risk involved in the decision. *Ambiguity aversion* denotes the dislike decision makers have for choosing between gambles with unknown characteristics. This involves missing relevant information about the distribution of an uncertain event as well as contradictory evidence or information (e. g., expert opinions) on some matter or event, which might confuse people. Camerer and Weber (1992) provide an overview on studies analyzing the effects of ambiguity on decisions. An important factor for the level of ambiguity aversion are social effects related to the own competence compared to others, which Trautmann et al. (2008) call "fear of negative evaluation". The authors link this effect to several empirical findings regarding (retail) investor behavior. Since it seems likely that retail investors are faced with higher ambiguity than professional investors, they could be more prone to ineffective behavior reducing ambiguity, such as the home bias, i. e., buying stocks from companies they assume to know better (Kilka and Weber, 2000). Ambiguity aversion could also serves as an explanation for the usage of investment heuristics, such as Technical Analysis, since it offers the investor an alleged explanation and solution for handling the uncertainty that is involved when investing in stocks.

2.4 Retail Investor Trading

It is a long-standing puzzle why irrational trading behavior among retail investors persists despite the overwhelming empirical evidence of systematic underperformance over many decades. Various studies document that investment accounts of retail investors exhibit severe investment mistakes. One line of explanations for the suboptimal trading and investing activities mentioned in the literature considers the behavioral and psychological shortcomings introduced in the last section. In this section, empirical findings regarding retail investor trading are summarized in order to provide a context for the retail investor related results presented in Section 3.5 and Section 4.6.

Ultimately, the most important question for the analysis of investor trading is to what extent retail investors meet their investment goals. This implies the necessity of some normative theory that provides a framework on how (retail) investors should behave given their preferences. The latter section introduced concepts of preferences that imply behavior which is not consistent with fully rational behavior, such as the optimization of mean-variance returns. In particular the gambling and entertainment aspect seems tricky with regard to an evaluation of retail investor behavior, since it can basically justify any trading behavior as long as the investor states that the fun she had by trading provided at least as much utility as the losses from the realized underperformance cost. However, considering the saving and retirement provision scenario discussed in Section 1.1, at least some part of most retail investor portfolios should aim to maximize long-term returns. So the long-term performance of the overall retail investor population is an important indicator of the effectiveness of saving efforts of the population and as such has implications for their future prosperity.

In the following, I start by discussing retail investor performance in general. Then I consider more specific trading characteristics and biases that have an effect on the performance.

A wide range of empirical studies confirm that retail investors lose money by trading. Odean (1999) and Barber and Odean (2000) are the first to analyze the performance of retail investor based on a broad data set of discount brokerage accounts. They find that retail investors underperform the market, which is increasing in the turnover rate of the accounts. That is, more trading adds costs but earns no additional returns or reduces risk. The reported average portfolio turnover of 75% per year is astonishingly high given that the average yearly turnover rate of stocks traded on the New York Stock Exchange (NYSE) is also about 75%. Further characteristics found by the authors are underdiversification and the tendency to hold small, value stocks.

Similarly, Grinblatt and Keloharju (2000) show that Finnish investors (households) underperform compared to foreign institutional investors and tend to behave as contrarian traders, i. e., they buy losing stocks and sell winning stock based on a six months horizon. More recently, Barber et al. (2014) analyze the long-term performance of speculative retail investors (day traders) in Taiwan and show that the majority loses persistently. Less than 1% of traders in their sample are able to earn consistent excess returns that cannot be explained by luck.

Several other studies focus on the characteristics of retail investor trading and on the reasons of the observed underperformance. High turnover rates are confirmed by Daniel et al. (1998), Glaser and Weber (2007), and Grinblatt and Keloharju (2009), among others. The authors attribute excessive trading to overconfidence of investors and gambling intentions. Overconfidence causes retail investors to misinterpret signals as information (Odean, 1998b), to overestimate the precision of their return forecasts (Glaser et al., 2007), or, in general, to believe to be able to beat the market.

Entertainment and gambling as a motivation to trade has been documented in several studies (Kumar, 2009; Dorn and Sengmueller, 2009) and implies a preference for assets providing right-skewed payoffs (Han and Kumar, 2013). Kumar (2009, p.1891) reports substantial socio-demographic differences in the attrition for lottery-like stock, that is, "[p]oor, young, less educated single men who live in urban areas, undertake non-professional jobs, and belong to specific minority groups[...]" are more likely to trade lottery-like stocks. Similarly, Goetzmann and Kumar (2008) find significant differences in portfolio diversification with respect to socio-demographic characteristics. In Taiwan, the stock market is used as a substitute for lotteries as trading volume in stocks traded by retail investor decreases as the lotto jackpots increase (Gao and Lin, 2015).

As a group, retail investors tend to trade simultaneously, i. e., they herd (Kumar and Lee, 2006; Dorn et al., 2008). Since retail investor have very similar cognitive limitations and limited resources (information), the considered reasons for herding are usually related to the ways investors try to overcome these shortcomings. Similar information, e.g. media (Engelberg et al., 2011; Barber and Odean, 2008) or other attention grabbing events (Seasholes and Wu, 2007), (stock) familiarity biases (Keloharju et al., 2012), investor sentiment (Kumar and Lee, 2006) or information processing effects, such as alphabetical biases (Jacobs and Hillert, 2015) or rank order effects (Hartzmark, 2015), are common explanations for the herding behavior. Furthermore, related trading strategies like a focus on dividend stocks play a role (Graham and Kumar, 2006).

In general, the evidence on the positioning and the investment style is somewhat mixed, which presumably reflects different or superimposing intentions and investment heuristics that retail investors use. For example, Odean (1999) reports that retail investor tend to buy stocks that have considerably risen or fallen over the previous six months, while they tend to sell stocks that have risen in recent weeks, i. e., they act as contrarian trader in the short-run. Contrarian trading of retail investors is confirmed in a range of studies in different countries and asset classes (Goetzmann and Massa, 2002; Schmitz and Weber, 2012). Kaniel et al. (2008) additionally show that excessive buying (selling) of retail investors is associated with positive excess returns in the following month. On the other hand, momentum and feedback trading (Jegadeesh and Titman, 1993) is also attributed to retail investors (Dhar and Kumar, 2001) suggesting that there are groups of retail investor pursuing different investment styles.

This contradiction might be caused by opposed trading behaviors over different time horizons and the use of different investment heuristics, such as momentum trading, Technical Analysis, and fundamental analysis (e. g., price-earning ratios). The survey conducted by Hoffmann and Shefrin (2014) provides insights into strategies and objectives of retail clients of a Dutch discount brokerage. 'Capital growth' (ca. 40%) and 'entertainment & gambling' (ca. 40%) are the most important (main) objectives of the retail investors who conducted the survey, while 'building financial buffer' and 'saving for retirement' are in the focus of only a few investors (ca. 10% and 5%, respectively). These results are compared to a similar survey by Lease et al. (1974) and interesting differences appear (see Hoffmann and Shefrin, 2014, Fig.1). Specifically, the applied strategies seem to have shifted from fundamental analysis and professional advice towards Technical Analysis. Hoffmann and Shefrin (2014) further show that Technical Analysts sell less on reversals compared to others leading to a more positive relation to the momentum factor from a Carhart four-factor model, which are still negative[16], though. The usage of Technical Analysis and related behavior is discussed in more depth within Chapter 3.

One of the most widely known properties of retail investor trading is the so-called disposition effect. The effect denotes the behavior of investors to ride losing trades long and to sell winning positions early (Shefrin and Statman, 1985), which has been documented by Odean (1998a), Grinblatt and Keloharju (2000), among others. Furthermore, the disposition effect is a driver of correlated trading of retail investors

[16]The average retail investor using Technical Analysis is less contrarian than the average investor, who shows significant contrarian trading behavior.

(Barber et al., 2009). Dhar and Zhu (2006) identify cross-sectional differences in the disposition effect based on socio-demographic factors. Wealthy and financial literate investors are less prone to the effect.

Two major explanations for the disposition effect have been put forward. The first is related to the discussed contrarian positioning of retail investors. Since contrarians expect prices to revert (also called mean-reversion investing), they are reluctant to sell their losing stocks (as they expect profits), but do sell wining position (as they expect them to fall again). The effect amplifies as retail investors are usually not able to short stocks or other assets, so they must have bought a stock before they can sell it.

Second, reference dependence and loss aversion as implied by prospect theory preferences introduced in the last section is considered as an important driver of the disposition effect. Although loss aversion would imply that investors try to avoid or limit losses, the reference dependence to the initial buying price leads to the situation that investors are reluctant to close the position (sell) because this would mean the realization of 'bad utility'. Furthermore, (subsequent) gains from an already losing position add utility at a higher rate since the utility function is convex in the domain of losses. Similarly, initial gains are valued more with respect to the initial price compared to subsequent additional gains as the utility function is concave. Thus, an investor with prospect theory preferences will typically sell a winning position more likely than a losing one.

Another line of explanations for the observed underperformance of retail investors considers their trade implementation. In particular, whether the usage of passive compared to aggressive orders and market or limit orders makes a difference for the investor performance. In the sample of Barber et al. (2009), the usage of aggressive order drive losses retail investors incur. In contrast, Linnainmaa (2010) shows for Finnish investors that limit orders of retail investors suffer from being adverse selected. Kelley and Tetlock (2013) show that only aggressive retail investor orders predict firm news, i. e., these orders contain valuable information about future prices. Effects from biased limit order submissions and the tendency to cluster on round numbers are considered in Chapter 4. For example, Kuo et al. (2015) provide evidence that limit order prices can be used to assess the level of informativeness of an order.

2.5 Market Microstructure and Market Quality

"Market microstructure is the study of the trading mechanisms used for financial securities" (Hasbrouck, 2007, p.3). Since trading securities is an important factor for the prosperity of an economy, it is important to understand how the organization of trading on a market platform influences the market outcome (cf. Weinhardt et al., 2003). Trading mechanisms must be effective and reliable in order to build and maintain the trust of market participants into the market. Since financial markets highly depend on their network externalities to work successfully (e. g., to ensure liquidity), trust in the market is essential to maintain the externality effect. If trust in the (financial) system vanishes and liquidity dries out, the consequences can be detrimental as happened during the crisis of the market for subprime mortgages (Krugman, 2007), for example.

Empirical market microstructure research analyzes how dimensions of trading and market quality alter with respect to external and internal factors, such as changes in market organization (technical infrastructure, trading protocols), regulation, behavior of market participants, economical situation, and competition between markets. O'Hara and Ye (2011, p.463) define market quality as "a market's ability to meet its dual goals of liquidity and price discovery." Both aspects are naturally interdependent and also influenced by numerous other internal and external factors. Zhang et al. (2011) establish a framework for market quality of electronic (financial) markets that describes the measurement of market quality and its links to external and internal factors, which can influence market quality.

In this thesis, I specifically focus on the relation of participant behavior and dimensions of market quality. In the following, the considered dimensions of market quality and respective measurements are introduced. Extensive introductions to theoretical and empirical market microstructure are provided by O'Hara (1995) and Hasbrouck (2007), respectively. O'Hara (2015) discusses current findings and issues in market microstructure with respect to automatized financial markets and high-frequency trading.

Liquidity

Harris (2003, p. 394) defines liquidity as a market's "ability to trade large size quickly, at low cost, when you want to trade," which refers to depth, implicit and explicit trading cost, as well as to execution speed, among others. The latter strongly depends on the sophistication of the market's information system infrastructure and communication technology, which is not explicitly considered in this thesis.

Due to the various dimensions of liquidity, a formal measurement depends on the market model and the goal of the analysis (e. g., a comparison of market structures or trading protocols) but also on the type of trader, since different market participants can have different requirements for liquidity. In this thesis, the main research object is continuous trading on Xetra, which is organized as a limit order book market. Therefore, I introduce measures typically used in the literature to assess the liquidity of such a market.

Trading Activity

In limit order book markets trading activity, i. e., the amount of executed transactions, measures the demand for liquidity. Chordia et al. (2011) state "that a decline in [implicit and explicit] trading costs plays a role in the dramatic increase in trading" observed from 1993 to 2008. Hence, with regard to the above definition by Harris, increasing trading activity can also be a sign of increased liquidity supply.

Trading activity is measured as the number of trades, the number of executed shares (*volume*), and the value of executed orders (*turnover*). In some instances, the number or imbalance of liquidity demanding buy and sell orders are of interest. Since exchanges typically report only transactions (see Section 2.2.1), it must be inferred from the data whether a transaction was initiated by a liquidity demanding buy or sell order. This is also necessary for several measures of implicit trading costs. To infer the trade direction from Times & Sales data (tick-by-tick data), the classification procedure by Lee and Ready (1991) is applied. Figure 2.2 visualizes the procedure.

The above measures of trading activity are naturally interdependent, but can signal diverging behavior of market participants, e. g., when traders split their order into smaller pieces. Besides transactions, limit order submissions leading to updates of best

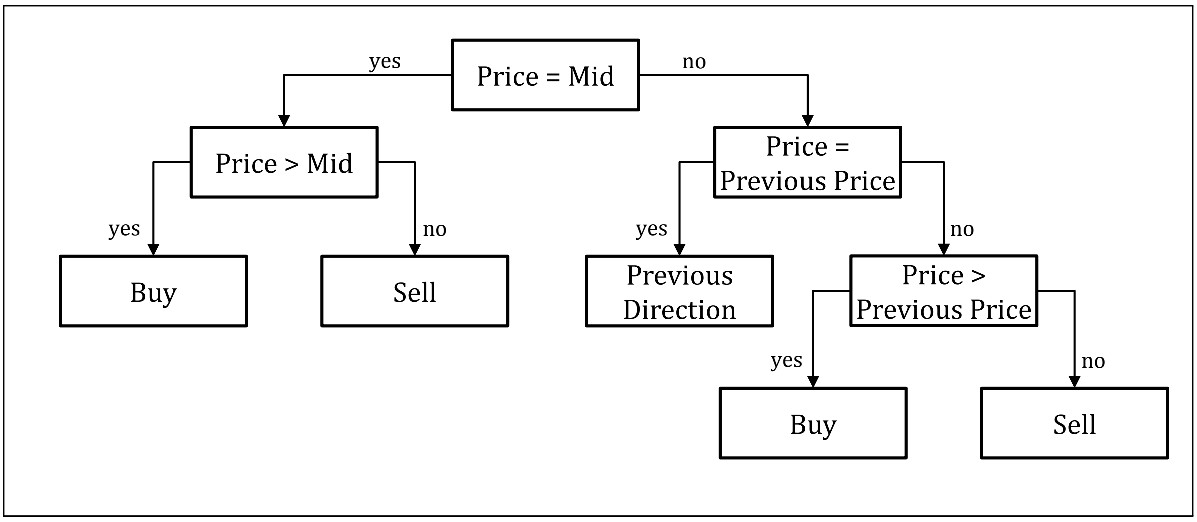

FIGURE 2.2: **Lee and Ready Classification Algorithm.** This flowchart illustrates the procedure proposed by Lee and Ready (1991) to classify trades in market data into liquidity demanding buy and sell orders. Starting point is the observation of a transaction price (*Price*) and the prevailing mean of the prevailing bid and ask price (*Mid*).

bid and ask or other levels of the limit order book measure market activity, which in modern financial markets is associated with high-frequency and market making activity. As discussed in Section 2.2.1, quote data from Thomson Reuters Tick History might provide an incomplete view on quote updates in order to reduce the size of data.

Implicit Transaction Costs

Implicit trading costs measure the cost of liquidity demander for demanding immediacy. The *Quoted Spread* measures the hypothetical transaction costs based on the prevailing best bid and ask, which is only valid for small trades or, more precisely for trades that are not larger than the offered volume. The measure is calculated with respect to the observed bid price Bid_t and ask price Ask_t of some stock and stated in basis points.

$$\textit{Quoted Spread}_t = 10,000 * (Ask_t - Bid_t)/(2 * Mid_t), \tag{2.1}$$

where $Mid_t = (Ask_t + Bid_t)/2$ denotes the midquote. Obviously, the measure changes as bid or ask price change, i. e., measuring at discrete points of time can bias the average measure since substantial variation between the measurement points could be omitted. Thus, I calculate the measure from tick-by-tick data and weight the observations by the duration the quote is valid in order to obtain an aggregated measure over some time period (e. g., one trading day).

Effective Spreads measure the actual transaction costs of executed trades. Hence, it is necessary to know the trade direction (buy or sell) of the demanding order. For trade i at time t the measure is defined as

$$\textit{Effective Spread}_{i,t} = 10{,}000 * D_i * (Price_{i,t} - Mid_{i,t})/Mid_{i,t}, \tag{2.2}$$

where $Mid_{i,t}$ denotes the midquote prevailing before trade i was executed. The effective spreads can be larger than the (prevailing) quoted spread, if the demanded volume is larger than the quoted volume, i. e., the trade 'walks up' the book and realizes an inferior average price. However, effective spreads can be smaller compared to lit quotes, if hidden limit order volume exists in the book. When considering average spread measures over some period (e. g., a trading day) the timing of orders can play a role, i. e., if traders primarily demand liquidity when it is cheap (small quoted spreads), average effective spreads can be smaller than quoted spreads. For these reason, it is insightful to consider both measures for an empirical analysis.

In order to account for the impact of liquidity demanding trades in the calculation of spread costs, *Realized Spreads* evaluate spread costs with respect to quotes some time after the trade. The measure is defined as

$$\textit{Realized Spread}_{i,t} = 10{,}000 * D_i * (Price_{i,t} - Mid_{i,t+x})/Mid_{i,t}, \tag{2.3}$$

where typical choices for the time lag x are 1, 5, and 15 minutes. The measure is usually interpreted as the liquidity suppliers' revenue, because if (quoted) prices do not revert after the trade or even move in the direction of the trade, it is likely that the demanding order was informed. Hence, the supplier has traded at an inferior price and the realized spread of the liquidity demander is small.

Orderbook Depth

The amount of liquidity supplying limit orders available at a point of time is referred to as *Depth*. Depth is usually calculated over both sides of the limit order book, that is, the available order volume (in Euro) on the bid and ask side:

$$Depth_t = Bid_t * BidVol_t + Ask_t * AskVol_t, \tag{2.4}$$

where $BidVol_t$ ($AskVol_t$) denotes the number of shares available on the bid (ask) side of the book. The depth measure can be extended to include more levels of the limit order book. Then, $DepthX$ denotes the cumulated depth on the first X levels of the limit order book, i. e., the X best prices. Cumulated depth is important for traders who want to trade (demand) large sizes at a reasonable price. In practice single trades rarely penetrate more than one level of the book, however. Nevertheless, depth on higher levels of the book can be insightful with respect to slower traders who do not continuously monitor bid and ask price movements and submit less aggressive orders.

Price Discovery

Price discovery means the ability of a market to determine the true fair value of the traded asset. Both the quality of price determination, i. e., the absence of price deviation from the fair value (pricing error), and the speed at which new information is incorporated into prices is of importance. The analysis of price discovery also considers the channel through which new information comes into prices. For instance, whether prices become more informative by liquidity demanding trades enforcing the fair price or by liquidity supplier who adjust their offered liquidity based on new information (quote-based price discovery).

In the context of price discovery, the efficient market hypothesis naturally plays a role. The efficient market hypothesis provides a normative framework on how we expect efficient prices should behave such that deviations to that behavior can be analyzed. In practice, it is evident that prices cannot always be fully efficient and the market needs some time to adjust to new information. Hence, a consideration of market efficiency depends on the time horizon. On a nanosecond basis different factors play a role compared to a daily or monthly consideration. Consequently, there exist different approaches to measure price discovery and price efficiency in these cases.

A way to measure the informativeness of a liquidity demanding trade is the so-called

Price Impact, which is defined as

$$PriceImpact_i = 10,000 * D_i * (Mid_{i,t+x} - Mid_{i,t})/Mid_{i,t}, \tag{2.5}$$

where x specifies the duration after a trade to which the midquote is compared. Typical values for the lag are 1, 5, and 15 minutes, but the actual choice depends on the type of security, whereby for more liquid stocks shorter intervals should be considered.

Other approaches to assess the information content of trades (and quotes) apply econometric models to the trade and quote time series, e. g., Vector Autoregressive Models (VAR) of quote revision (midquote price changes) and trading volume (Hasbrouck, 1991b,a). The model measures the impact of lagged trades (volume) on the quote revisions, which is interpreted as the information content of these trades. Furthermore, the model can be used to obtain a volatility decomposition of the total volatility of price changes (i. e., the observed variance of the assumed random walk) into permanent (information related) volatility and transitory volatility (noise).

In a more recent approach proposed by Menkveld et al. (2007), price changes are decomposed into permanent and transitory components by the application of State Space Models (SSM), which model the observed midquote as an unobserved efficient price and a pricing error. The SSM methodology is introduced and applied in Section 3.6.5.

To assess price efficiency over longer horizons, there are several price based measures that aim to detect deviations from the random walk (martingale) property as postulated in the efficient market hypothesis. In contrast to VAR models, measures are calculated on the basis of (low-frequency) price observations and are easier to calculate over long periods compared to VAR models or similar. I introduce and apply three measures of informational (in)efficiency in Section 3.6.4.

Chapter 3

Technical Analysis

3.1 Introduction

Technical Analysis (TA) has a long history in security analysis and its roots date back to the invention of the Dow Theory in the late 19th century which is considered as the foundation of Technical Analysis. The main approach of most Technical Analysis methodologies is to analyze historical price and volume data regarding regularities and other 'typical' developments, which can be used to infer signals about future prices. Many Technical Analysis concepts base on the idea that market prices behave cyclically or move in trends. Thus identifying trends and trend reversals is considered as a major task for the Technical Analyst as pointed out in popular textbooks on Technical Analysis (e. g., Bulkowski (2011); Murphy (2011); Kirkpatrick II and Dahlquist (2012)).

Originally, the identification of Technical Analysis trading signals (TA signals[1]) is based on the visual recognition of predefined patterns in price and volume charts, or on some transformation of the data, such as (moving) averages of prices. To give an example, Figure 3.1 shows the so-called head-and-shoulder pattern which shall signal a reversal of an uptrend towards a downtrend. Consequently, the trigger of a head-and-shoulder pattern implies to sell the security. Similarly, Technical Analysts use

[1] Henceforth, I use the abbreviation *TA signal* to denote explicit trading signals (recommendations) to buy or sell a security based on the application of some Technical Analysis strategy. The latter shall denotes an explicit calibration of some Technical Analysis technique. That is, moving averages are an example for a Technical Analysis technique and the 200-day moving average is an explicit Technical Analysis strategy of that technique generating TA signals.

the moving average of the most recent price observations indicating the begin of an uptrend (downtrend) if prices cross the moving average from below (above).

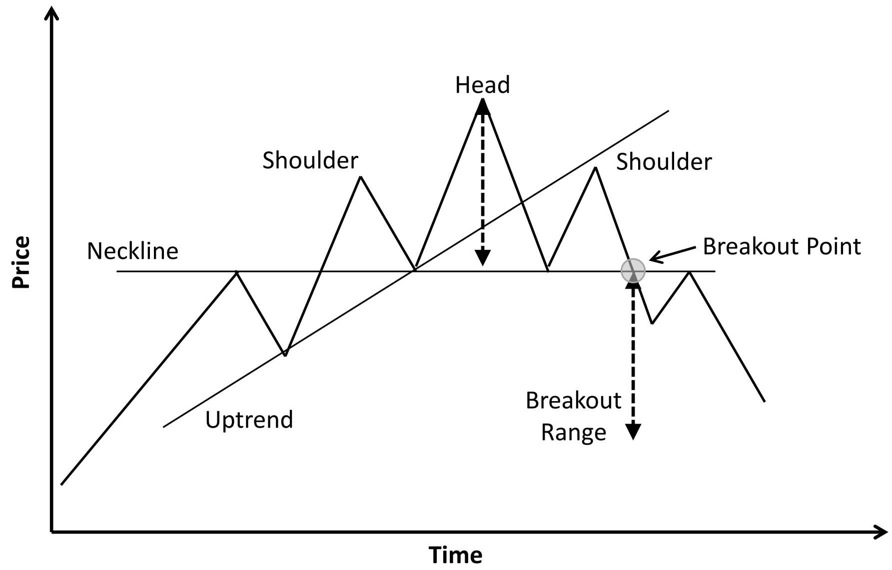

FIGURE 3.1: **Head-and-shoulders Chart Pattern.** The figure shows an exemplary illustration of the so-called head-and-shoulders chart pattern. The pattern indicates a trend reversal from an uptrend to a downtrend. The breakout point constitutes the actual trading signal to sell the security. The illustration is based on the definition given by Technical Analysis textbooks (cf. Bulkowski, 2011, p.405).

A major problem for the financial economist arises from the vague definition of trading strategies since Technical Analysts are usually reluctant to provide explicit implementations of the proposed strategies. What data and observations frequency should be used? How are methods and parameter supposed to be calibrated explicitly? Which combination of methods is advisable? What shall be done if method A suggests to buy while method B suggests to sell? The authors of Technical Analysis textbooks argue that the investor must find the tools that fit to her investment style, her goals, and her time-horizon, for example. While this statement might be a fair recommendation in general, it obliviously gives the authors room to put forward recommendations which are hard to falsify by means of quantitative analyzes. Statistical evaluations in Technical Analysis textbooks mostly provide assertions of the type "strategy S worked in X% of the cases over the last N years". Hence, such evaluations should be considered as descriptive at best.

In their consideration of Technical Analysis, Lo et al. (2000) state that "one of the greatest gulfs between academic finance and industry practice is the separation that exists between technical analysts and their academic critics". From my experience, this still seems to be true today. An important difference between academics and practitioners considering some profitable strategy is the 'why'. While a practitioner might argue some profitable strategy works as long as it works, the financial economist is primarily interested in the question why some strategy is actually profitable, i. e., are there any risks involved explaining excess returns; is there some form of market anomaly or mispricing, or is the original claim of profitability just based on a flawed analysis?

Hence, academics have put much effort in the analysis of the profitability of Technical Analysis strategies. I review these results in Section 3.3 in more detail. In sum, the evidence regarding profitability is mixed. Although profitability is an interesting question as it would constitute an anomaly to the widely accepted weak form of the efficient market hypothesis, I argue that for the research presented in this chapter it plays no crucial role whether Technical Analysis is profitable or not. However, I show that it can matter for the market outcome, e. g., in terms of trading activity, market liquidity, and (short-term) price discovery.

As mentioned above, Technical Analysis is basically as old as the stock market itself, but there has been an important change during the last two decades, namely the electronic evolution of financial markets. The digitalization of financial markets and the financial service industry enabled real-time access to markets and market data for basically any person with an internet connection. Especially for online (discount) brokers, Technical Analysis is an interesting way to get their clients into trading. As outlined in Section 1.1 and 2.4, retail investors are faced with a complex decision making problem when investing in financial markets. Compared to institutional investors, their cognitive and technical resources to solve this problem are much more limited.

A major service of brokers is to support their clients with solving their investment problem. Online brokerages typically do so by providing appropriate information systems, market access, data as well as data visualizations (e. g., chart tools). Many brokers offer access to more detailed data sources for additional fees. While providing data is basically neutral and provides clients with general market information, (discount) brokers have an intrinsic motivation that their clients trade frequently due to the trade-based fee structures. To get clients into trading, Technical Analysis could be a promising tool for brokers as it provides explicit trading recommendations and thereby it 'helps' the client with selecting the instruments to trade, specifying the trade direction, and defining some exit strategy to close the trade. In fact, there are software providers[2] which distribute tools for chart analysis and automatic detection of Technical Analysis trading signals of various types. Interestingly, these tools are offered (to brokerages) for "engaging and monetizing your account holders"[3].

If the above slogan is true and retail investors actually use Technical Analysis, the question arises whether Technical Analysis is a relevant factor for the decision making of retail investors and what impact Technical Analysis has on their trading efforts. Since professional investment advice from bank advisers or wealth managers is expensive, particularly for small accounts, trading recommendations from Technical Analysis seem cheap and easy to use for any investor. On the other hand, related strategies could be perceived as complex enough to be considered as a form of serious investment analysis providing a certain degree of validity compared to a buy-and-hold strategy or a random approach.

The German market of speculative structured products is a promising research object to analyze a potential relation between Technical Analysis and retail investor trading. The unique data set provided by Börse Stuttgart allows for a precise consideration of trading in structure products since it contains full trade and orderflow information. Analyzing this data, I find a significant increase in trading activity on days of Technical Analysis trading signals of various types. The increase in activity reverses on the following trading days. Furthermore, I identify trading characteristics of round-trip trades. First, raw returns in TA-related trades are significantly higher, while the leverage level selected at purchase is lower and the holding duration tends to be shorter. Second, the shape of the realized return distribution is significantly less left-skewed (more

[2]For example, the German software provider TraderFox GmbH (www.traderfox.de) and the Canadian company Recognia Inc. (www.recognia.com) develop chart analysis tools for brokerages and other information providers.

[3]Quote taken from https://www.recognia.com/, accessed on June 19, 2016.

right-skewed).

The presented analysis provides further evidence that Technical Analysis plays a role for retail investors. On the other hand, there is evidence regarding professional investors, such as fund mangers, who rely on Technical Analysis to some extent. For instance, Menkhoff (2010) documents that for 18% of the surveyed institutional investors Technical Analysis is the preferred way of information processing and 87% do at least consider it beside other things. Furthermore, there is evidence that trading activity on major stock markets is related to Technical Analysis trading signals (Kavajecz and Odders-White, 2004; Bender et al., 2013; Etheber, 2014). Since Technical Analysis is primarily based on past price and volume information, trading on technical analysis can be considered as noise trading if we assume markets are (weakly) efficient in the sense of Fama's efficient market hypothesis. If Technical Analysts account for a relevant amount of trading volume, prices and market quality could be affected as "the price of a stock reflects both the information that information traders trade on and the noise that noise traders trade on" (Black, 1986, p.532). Thus, I assess whether trading signals derived from popular Technical Analysis strategies are related to various dimensions of market quality on the major German stock market Xetra.

Indeed, I find that several dimensions of market liquidity are affected by the considered trading signals. However, some findings are in contradiction to the expected results derived from previous findings in the literature.

The results presented in this chapter contribute to the literature as follows. First, it adds to the literature on retail investor trading and behavior by showing that trading speculative financial products is related to Technical Analysis. In particular for literature considering the German market of structured products, this is a novel finding and adds a new information dimension that is used for trading, because existing studies only considered (corporate) news, earning announcements, and various product characteristics. Secondly, the analysis of the effect of Technical Analysis on (stock) market quality based on intraday data and along typical dimensions of liquidity provide new insights regarding this relationship. Additionally, the chapter provides first evidence that price discovery is actually related to Technical Analysis trading signals.

The remainder of this chapter is organized as follows. Section 3.2 motivates the research questions of this chapter. Section 3.3 provides an overview of the academic literature on Technical Analysis with a focus on the potential profitability of related strategies. The methodological approach used to analyze Technical Analysis, i. e., the definition and recognition of TA-related trading signals, is introduced in Section 3.4. Section 3.5 discusses the role of Technical Analysis in retail investor trading and constitutes the first part of main results presented in this chapter. Section 3.6 presents the second part of main results focusing on the relation between Technical Analysis and market quality in DAX30 stocks traded on Xetra. Eventually, Section 3.7 concludes.

3.2 Research Questions

Chapter 3 of this thesis explores the meaning of Technical Analysis for securities trading. I address two main research questions which consider trading on the market of structured products and the stock market, respectively.

> **Research Question 1.** *Do investment heuristics that are summarized as Technical Analysis influence retail investor trading in speculative structured products?*

To make this question more tangible with respect to specific research objects I break it down into two sub-questions. The first part seeks to substantiate the potential relevance of Technical Analysis for retail investors trading. Since Technical Analysis subsumes a vast range of different techniques the following sub-questions shall specifically refer to chart patterns and moving average strategies, which will be defined in Section 3.4.

> **Research Question 1a.** *How are trading signals from Technical Analysis related to trading activity in structured products on a retail investor dedicated market?*

Technical Analysis gives investors quite precise trading recommendations compared to other investment styles and existing research suggests that Technical Analysis (more precisely moving average strategies) – if followed strictly – provides an different outcome in terms of expected returns compared to a buy-and hold strategy, for instance. Thus, basic characteristics of (round-trip) trades might be affected.

> **Research Question 1b.** *What are characteristics of trades which have been initiated in accordance to Technical Analysis signals and do these characteristics differ from other trades?*

Admittedly, the market of structured products is rather small compared to the stock trading segment on Xetra which exceeds the turnover on Stuttgart Stock Exchange many times over. Furthermore, the different market structure of Xetra and its greater generalizability with regard to stocks markets world-wide allow for a broader perspective on the relevance of Technical Analysis for financial market. Contrary to trading of structured products on Stuttgart Stock Exchange, Xetra is the primary trading venue for German stock companies and as such has an important price determination function for the economy. Thus the relation between Technical Analysis and stock pricing is of special interest which leads to the following research questions.

Research Question 2. *What is the relation between Technical Analysis trading signals and the market quality on Xetra?*

More specifically, I assess whether trading signals derived from the Technical Analysis techniques moving averages as well as support and resistance levels are related to various dimensions of market quality. The following three sub-questions sharpen the considered dimensions of the main research question and provide a structure for the presented research approach.

Research Question 2a. *What is the effect on dimensions of liquidity supply and demand around Technical Analysis trading signals?*

To answer this question, I analyze various dimensions of liquidity such as trading activity, spread measures, and limit order book depth and assess which dimensions are related to the considered Technical Analysis signals. If liquidity supply and demand is influenced in any direction, price efficiency could be as well which is addressed by the following questions.

Research Question 2b. *Is there a relation between Technical Analysis trading signals and measures of informational efficiency, i. e., do price processes show characteristics associated with inefficient prices?*

Research Question 2c. *Given that technical traders are uninformed noise traders, what is the effect on transitory and permanent price components when Technical Analysis trading signals appear?*

3.3 Academic Perspective on Technical Analysis

Academic research on Technical Analysis and related strategies has a long history dating back to the early nineteen-sixties when, among others, Alexander (1961) examined whether filter rules were able to earn excess returns in the U.S. stock market. The author – and other authors alike – argues that excess returns generated by strategies based on past price information contradict the assumption of prices following random walks (or, more general, having martingale properties). Since excess returns based on past price information are a contradiction to the three forms of efficient capital markets hypothesized by Fama (1970), many papers studied Technical Analysis and related strategies to test market efficiency. In the following decades, several papers analyzed different strategies with mixed results, e. g., James (1968), Jensen and Benington (1970), and Irwin and Uhrig (1984).

An important factor in the analysis of profitability is how trading costs are incorporated. Considering a perfect market in a mathematical sense, i. e., a market without transaction costs consisting of a risk-free asset and a risky asset following a random walk which both are priced such that no arbitrage is possible, then there is no trading strategy with limited capital requirement that earns risk-adjusted excess returns. However, there is also no strategy in this market that underperforms since the opposing strategy would earn profit. An important implication for the real-world investor in an efficient market is the fact that in this scenario any kind of trading costs are the major reason for systematic under-performance compared to market returns. This has been pointed out by many financial economists when discussing how retail investors should improve their trading approaches (e. g., Barber and Odean, 2000; Bauer et al., 2009; Meyer et al., 2014).

So a crucial point for studies which focus on the profitability of TA-related trading strategies is how trading costs and trading frictions are incorporated. Park and Irwin (2007) provide a literature review on the profitability and conclude that profitability must be seen skeptical as trading costs can be hard to measure ex post. The authors review 95 'modern' studies beginning from 1988. The often cited[4] study by Brock et al. (1992) is considered as one of the first 'modern' analyses and "provides strong support

[4]As of June 17, 2016, Google Scholar reports 2107 citations. It is one of the most cited papers on Technical Analysis.

for the technical strategies" based on daily data of the Dow Jones Industrial Average Index over a 100-year period. Similar to this thesis, moving average and trading range break-out strategies (which are similar to support and resistance levels) are examined.

Although Brock et al. (1992) and 55 other studies find positive evidence regarding Technical Analysis profitability, Park and Irwin (2007) question whether all of these results are thoroughly reliable. Besides trading costs, they mention risk estimation and data snooping as potential sources of biases. Data snooping occurs when profitable trading strategies are selected or calibrated within sample. Even if strategies are predefined, using a very large set, say thousands, of strategies, the chance is high to obtain positive results just by chance. Profitability can also evolve (over time) as a type of survivorship bias when many investors analyze a large universe of trading strategies and then narrow down the range of strategies based on their results, i. e., well-performing strategies receive more attention given they performed well in the past.

More recent papers show that some studies actually face data snooping biases implying that the considered Technical Analysis strategies are not persistently profitable. Sullivan et al. (1999) introduce a refined data snooping detection based on White's Reality Check bootstrap methodology (White, 2000). The purpose of the methodology is to rule out the possibility that some well-performing strategy is just chosen by luck while many others in the sample show no over-performance. The main idea is to resample historical returns to enhance the statistical power if some strategy actually has been profitable on the original data sample. Interestingly, Sullivan et al. (1999) can confirm the over-performance found by Brock et al. (1992), however out-of-sample performance on the following 10-year period is not persistent. The issue of persistence is further examined by Bajgrowicz and Scaillet (2012). They introduce an improved selection method, which is able to select outperforming strategies more consistently compared to previous studies. Yet these strategies are not able to earn out-of-sample excess returns (after trading costs), i. e., "investors would never have been able to select ex ante the future best-performing strategies" (Bajgrowicz and Scaillet, 2012, p.473).

In general, persistence of trading strategies is a highly discussed issue in research on security markets. An often mentioned aspect in the Technical Analysis literature is the potential self-destruction of any profitable trading strategies. Timmermann and

Granger (2004) argue that any stable forecasting pattern, i. e., any trading strategy that can predict future returns will ultimately disappear after it has been made public. So investors who are looking for new strategies and others adopting to them might cause strategies becoming profitable for some time.

Form a theoretical point of view, this mechanism fits within the adaptive market hypothesis put forward by Lo (2004). He suggests that the human nature seeks to constantly adapt to changing environment conditions, which could explain market anomalies, i. e., deviation from Fama's efficient market hypothesis. In this context, Neely et al. (2009, p.486) state that the time-varying profitability of technical trading strategies are "consistent with the view that markets adapt to evolutionary selection pressures".

If we consider financial markets as complex social systems of not fully rational participants, strategies like Technical Analysis could become self-fulfilling because a large group of market participants believes it is. If this belief is popular and 'opposing forces' (e. g., speculators who enforce efficient prices with respect to the fundamental value of an asset) are weak, anomalies in terms of excess returns could occur (cf. discussion of limited arbitrage in Section 3.6.1). The self-fulfilling property is also considered as an explanation why investors use Technical Analysis, that is, because they think others use it and, hence, Technical Analysis plays a relevant role as they try to imitate others (Taylor and Allen, 1992; Menkhoff and Taylor, 2007).

In this sense, behavioral aspects could play a dominant role regarding the usage and the effect of Technical Analysis in financial markets. Similarly, several behavioral explanations have been put forwards in case of the momentum anomaly. The success of momentum strategies, i. e., buying past winners and selling past losers, is a highly discussed yet accepted finding in the asset pricing literature (Jegadeesh and Titman, 1993). Similar to Technical Analysis, it is related to trends in prices. Thus, it is hard to infer what inter-dependencies between momentum (trading) and Technical Analysis might exist. Given the definitions of momentum trading and Technical Analysis, one could eventually cause the other to be profitable in certain situations (e. g., trend-following Technical Analysis strategies), but momentum can be considered as a more general concept. First, momentum strategies are often less complex than Technical Analysis related strategies. Second, there are drivers and explanations that are not directly related to trading on momentum strategies, but can cause momentum in asset returns (e. g., fund flows, herding, liquidity risk, etc.).

The scope of discussions and analyses in the asset pricing literature (and other finance areas) regarding momentum is too far-reaching to be summarized within this thesis[5]. One branch of explanations motivates behavioristical reasons for the momentum anomaly. For instance, Barberis et al. (1998) argue that the representative heuristic mediates momentum as investors extrapolate past returns. In a similar way, Daniel et al. (1998) motivate overconfidence of investors as an explanation for short-term momentum and long-term reversals in asset returns. Grinblatt and Han (2005) show that prospect theory preferences and mental accounting (disposition effect) can explain momentum in asset prices since after controlling for unrealized capital gains past returns have no predictive power anymore. Although these arguments constitute only one branch of explanations for the momentum effect, it demonstrates the influence of behavioral aspects on asset prices and returns. This motivates the potential role of behavioral aspects for Technical Analysis and price determination. Further literature that considers the behavioral aspect as well as the potential impact on the trading outcome is discussed in Sections 3.5.1 and 3.6.1 in detail.

Summarizing, this overview highlights the controversial discussion and perception of Technical Analysis in the academic literature. To some extent, the question of profitability has been answered inconsistently. While this might be due to adaption of investors and markets leading to time-varying results or to relations which are hard to proof by means of statistical analyses, the question of profitability is not a focus of this thesis. I assume that some investors use Technical Analysis – whether profitable or not –as a motivation to investigate the research questions postulated in the previous section. Since these research questions consider the impact of such trading activities, it is only of subordinate importance whether this behavior is actually rational in the sense of statically significant and persistent excess returns.

[5]For a broader discussion of momentum in asset prices see, among others, Subrahmanyam (2007, ch.2), Novy-Marx (2012), Fama and French (2012), and Moskowitz et al. (2012).

3.4 Recognition of Technical Analysis Trading Signals

The foundation for a scientific analysis of Technical Analysis is to identify and to reconstruct trading techniques and corresponding signals which Technical Analysts postulate to be relevant for security prices. This involves three tasks. First, the development of methods to identify chart patterns and other trading rules in price series. Second, the selection and explicit definition of the Technical Analysis techniques. Third, the calibration of these techniques since typically several parameters are needed to describe the visual appearance of a pattern, the length of the considered time period, etc.

The universe of Technical Analysis techniques and related strategies is immense. For example, the popular handbooks on Technical Analysis by Bulkowski (2011) or Kirkpatrick II and Dahlquist (2012) describe countless strategies and signals that could be considered, yet there these are only two books in many. In this thesis, I focus on three different classes of Technical Analysis techniques: chart patterns, support and resistance levels, and moving averages. I keep the number of pattern types and moving averages relatively small and specific in their calibration in order to obtain a narrow set of trading signals. Due to the fuzziness of the recognition and definition of Technical Analysis techniques, I intend to use the most popular ones in order to capture as many Technical Analysis traders as possible. This section describes the algorithms used to detect trading signals from Technical Analysis.

3.4.1 Moving Averages

A well-known Technical Analysis technique are moving averages (MA). More precisely, the average of recent prices which is calculated over a certain period of time and iteratively updated after a new price observation realizes. Moving averages are not only used by Technical Analysts but are displayed in many financial charts in media or trading tools. On the other hand, moving averages have already been proposed in the 1950s and earlier as the citations in James (1968) show. Although the implementation of moving averages is relatively simple compared to other Technical Analysis techniques, the selection of a moving average type and the calibration of parameters introduces a high level of uncertainty regarding the actually applied methods. For instance, there are different types of moving averages, like simple, exponentially-weighted, truncated, or filtered moving averages, which basically use different weights to calculate the average. Furthermore, the number of observations used for averaging as well as the observations frequency, e. g., daily, weekly, etc., results in many calibration dimensions. Lastly, the actual signal trigger condition can vary. In the simplest case a buy (sell) signal occurs if the price breaks its average from below (above) but often further conditions like filter bands or a second, shorter moving average is used to reduce the effect of so-called whiplash or whipsaw signals when prices fluctuate around their mean.

In this thesis, I use several types of moving averages but keep the number of different calibrations small. The motivation behind the specific choice of moving average comes from the impressions of moving averages available in financial media and trading tools which usually have pre-defined lengths like 200 days, 50 days, and so on. The set of moving averages covers simple moving averages (SMA) of different lengths with and without 0.1% filter bands. Additionally, I consider 20-day/100-day dual (simple) moving average crossover (DSMA), and 50-day/200-day DSMA.

The 200-day simple moving average with 0.1%—filter generates a buy signal on day t if $SMA^{200}_{t-1} > P_{t-1}$ and $P_t > 1.001 \times SMA^{200}_t$, and a sell signal if $SMA^{200}_{t-1} < P_{t-1}$ and $1.001 \times P_t < SMA^{200}_t$, where SMA^{200}_t denotes the arithmetic mean of $P_t, ..., P_{t-199}$. The filter bands shall reduce the number of so-called 'whipsaw' signals when prices are moving closely around the moving average. Analogously, SMA with other lengths and filters can be calculated straightforward.

Dual moving average crossover generate buy (sell) signals when the shorter moving average crosses the longer from below (above). That is, a buy signal of a 20-day/100-day dual moving average occurs if $SMA^{100}_{t-1} > SMA^{20}_{t-1}$ and $SMA^{20}_t > SMA^{100}_t$, and a sell signal if $SMA^{100}_{t-1} < SMA^{20}_{t-1}$ and $SMA^{20}_t < SMA^{100}_t$.

Naturally longer moving averages and larger filter bands generate fewer signals. In general, it is not expedient for the empirical analysis to use a huge universe of strategies because this might lead to data snooping issues. For a large set of trading signals, the chance is high to find some result for some strategy just by chance. On the other hand, using very uncommon strategies, e. g., a 273-day moving average, might reduce the observed effect strength if many signals are 'false signals', i. e., signals which are not used by the majority of Technical Analysts.

3.4.2 Chart Pattern Recognition

Contrary to moving averages, one cannot simply calculate chart patterns from price data since the widely postulated definitions of chart patterns (e. g., Bulkowski, 2011) involve visual recognition of certain patterns in the drawn price graph. Thus even the way of drawing the chart has the some influence on the result of the recognition. A wide-spread form of visualizing price data are so-called candlestick charts which in addition to the last trade price in some observation interval (e. g., one trading day) contains information on the first as well as highest and lowest price in the respective interval. Figure 3.2 shows an example of such plot taken from the trading platform SAXO trader[6] by Saxo Bank A/S.

Most chart patterns are defined by a sequence of highs and lows (also called peaks and troughs) followed by a trigger condition. Obviously, the additional information on the highest and lowest trade price within a time interval, which is displayed in the candle stick chart, can substantially change the exact location of a high or low in the (drawn) price graph. In a first step, I focus on chart patterns based on daily data. Because of this coarse granularity of observing patterns and associated signals, the consideration of other price information than the closing price is of subordinate importance for the recognition of chart patterns. In Section 3.4.3 the recognition is refined for intraday data to allow for a higher signal precision.

The main idea of the pattern recognition used in this thesis is based on the seminal paper by Lo et al. (2000) who use smoothing techniques to identify chart patterns. Chart patterns are defined by a sequence of highs and lows and a trigger price condition. The smoothing tries to capture the eye-balling of a human trader to reduce the noise in the price movement which enables the identification of 'significant' local highs and lows in the price chart. Analogously to Lo et al. (2000) and Savin et al. (2006), I use kernel

[6] See `http://www.saxobank.com/saxotrader` (accessed on August 16, 2016) for a description of the SAXo trader online trading tool.

FIGURE 3.2: **Candlestick Chart of Deutsche Bank Stock Prices.** The figure shows an example for a candlestick chart based on Deutsche Bank stock prices from July 2011 to November 2011 drawn in Saxo Bank's Saxo Trader tool. Each candle represents one trading day. A green (red) candle signals that the closing price is higher (lower) than the opening such that the bottom edge of the candle body refers to the opening (closing) price and the upper edge refers to the closing (opening) price. The thin lines mark the trading range during the trading day, i. e., the line ranges from the highest to the lowest trade price. Furthermore the figure shows an example of a head-and-shoulder pattern highlighted by the manually drawn hats and the vertical line. The pattern consists of three subsequent highs of which the outer once are of similar height but visibly lower than the one in the middle. The (approximately) vertical line defined by the two lows between the highs is called neckline. If the price eventually falls below the neckline a sell signal is triggered.

regressions to reduce the noise in some price series $P_t, t = 1, \ldots, n$, i. e., the so-called Nadaraya-Watson estimator is applied to obtain the smoothed series

$$m_t = \frac{\sum_{j=1}^{n} P_j \times K_h(j-t)}{\sum_{j=1}^{n} K_h(j-t)}, \tag{3.1}$$

where $K_h(\cdot)$ is the Gaussian Kernel

$$K_h(x) = \frac{1}{h\sqrt{2\pi}} \exp^{-x^2/2h^2},$$

with bandwidth parameter $h > 0$. Then all local extrema in the smoothed series $m_t, t = 1, ..., n$ are determined, i. e., all $k \in \{2, ..., n-1\}$, satisfying $m_{k-1} < m_k$ and $m_k > m_{k+1}$ for a local high and vice versa for a local low. The actual local extremum is defined at the maximum (minimum) of the actual prices around k, i. e., $E_i = \max(P_{k-1}, P_k, P_{k+1}), i = 1, 2, ...,$ where i numbers the sequence of extrema. The procedure based on the smoother Kernel ensures that the sequence $E_i, i = 1, 2, ...$ always consists of alternating highs and lows since the Kernel is a continuous function.

The above procedure is carried out on a moving window of fixed length. The window length restricts the duration over which patterns can evolve but it is only of subordinated importance for the number of patterns found given the degree of smoothness defined by parameter h is not extremely high. The analysis of daily data runs on rolling windows of 84 (trading) days, which represents about four months. This seems to be sufficient assuming that traders using daily price observations usually do not search for long-term patterns evolving over multiple years. Furthermore, the instruments considered in the analysis of retail investor trading in Section 3.5 are typically used for short-term trading.

In general, the window length must not necessarily conform to the price window which a trader would use in practice since it only restricts the maximum possible length of a single pattern, i. e., the distance between the first and last price involved in the pattern. The last extremum in the sequence defining a pattern must be the 75$^{\text{th}}$ observation in the window, which leaves nine observations subsequent to the trigger point. The latter ensures that there are enough input observations for the kernel regression in order to avoid boundary effects on smoothed prices in the range of the pattern. The requirement of a single trigger point ensures that each occurrence of a pattern is only found once.

The most influencing factor in the above procedure is the bandwidth parameter h which defines the degree of smoothing. A large value of h results in fewer detected extrema and thus fewer patterns. It also influences the average duration of patterns since more extrema in a fixed time window allow patterns to evolve over a shorter period of time. Lo et al. (2000) and related papers use cross-validation to determine the value of h. Cross-validation determines h by minimizing the overall squared error when using the model to sequentially predict an observation by all others. The approach is also called 'leave-one-out method'. However, my tests applying cross-validation tends to produce some undesirable calibrations for the purpose of detecting chart patterns.

First, h becomes relatively small which is why other studies (e. g., Savin et al., 2006) use multiples of h to increase the degree of smoothing. In general, it is not surprising that the procedure results in small h values. If we assume the price series to be close to random walks (without trend), the best place to look for the left-out price observation within the cross-validation procedure would be between the two adjacent observations. Therefore most of the weight is given to these observations, i. e., the bandwidth h becomes very small such that the Kernel estimate of the left-out observations is approximately the average of its adjacent neighbors.

Secondly, if determined by cross-validation the value of h varies quite much from window to window, which I believe is not practical in the sense that traders probably do not change their visual (eye-balling) or algorithmic recognition calibration when a new observation updates the price graph. Furthermore, strongly varying h can lead to the situation where a detected pattern is not detected in the next window which would be inconsistent to some extent, even when repeating patterns are excluded due to the trigger condition. Nevertheless, I share the view that traders might change their cognitive degree of smoothing, for example when prices are more volatile (cf. Lo et al., 2000, p.1710). Thus, for each window i let $h_i = 1 + 8\sigma_i$, where σ_i denotes the standard deviation of the price differences in window i. This definition results in a similar average of h as in the cross-validation case with multiplier 3.0 but comes with much less variation (in h) between windows and almost no jumps.

Chart Pattern Definitions

I consider three types of chart patterns each including a long (buy signal) and a short (sell signal) version: (inverse) head-and-shoulders, double top & bottom, and rectangle top & bottom. The pattern definitions are derived from the academic literature and all include a so-called neckline-conditions which Kirkpatrick II and Dahlquist (2012) describe as an important aspect for the pattern validity.

The *head-and-shoulder* pattern (see Figure 3.1 for an illustration) requires a sequence of extrema $E_1, ..., E_6$ such that

- E_1 is a maximum
- $E_3 > E_1$ and $E_3 > E_5$ (head above shoulders)
- $|E_i - \bar{E}| \leq 0.015 \times \bar{E}$, for $i = 1, 5$, where $\bar{E} = (E_1 + E_5)/2$ (shoulders have similar height)
- $|E_i - \bar{E}| \leq 0.015 \times \bar{E}$, for $i = 2, 4$, where $\bar{E} = (E_2 + E_4)/2$ (neck points are in similar range)

If the above conditions are satisfied, it is checked whether the price crosses the so-called neckline, which is defined by the line through E_2 and E_4. The sell signal (if any) is generated at the first price between $E5$ and $E6$ below the neckline.

Analogously, the *inverse head-and-shoulder* pattern is defined as

- E_1 is a minimum
- $E_3 < E_1$ and $E_3 < E_5$ (head below shoulders)
- $|E_i - \bar{E}| \leq 0.015 \times \bar{E}$, for $i = 1, 5$, where $\bar{E} = (E_1 + E_5)/2$ (shoulders have similar height)
- $|E_i - \bar{E}| \leq 0.015 \times \bar{E}$, for $i = 2, 4$, where $\bar{E} = (E_2 + E_4)/2$ (neck points are in similar range)

If the above conditions are satisfied, it is checked whether the price crosses the neckline, which is defined as the line through E_2 and E_4. The buy signal (if any) is generated at the first price between $E5$ and $E6$ above the neckline.

Let the function $d(\cdot)$ return the position of an observation within the window. *Double tops* are characterized by (not necessarily consecutive) extrema E_1, E_2, E_3 satisfying

- E_3, E_1 are maxima
- $d(E_3) - d(E_1) \geq 10$,
- $|E_i - \bar{E}| \leq 0.015 \times \bar{E}$, for $i = 1, 3$, where $\bar{E} = (E_1 + E_3)/2$
- $E_2 = \min_i(E_i : d(E_1) < d(E_i) < d(E_3))$
- $E_j > \max_i(E_i : d(E_1) < d(E_i) < d(E_3)), j = 1, 3$

If the above conditions are satisfied, it is checked if the price crosses the neckline, which here is defined as the horizontal line through E_2. The sell signal (if any) is generated at the first price after $E3$ below the neckline. *Double bottoms* are defined as inverted *double tops* and generate a buy signal.

Rectangle tops consist of five consecutive extrema $E_1, ..., E_5$ satisfying the following conditions:

- E_1 is maximum
- $1/1.01 < E_i/\bar{E} < 1.01,$ for $i = 1, 3, 5,$ where $\bar{E} = (E_1 + E_3 + E_5)/3$
- $1/1.01 < E_j/\bar{E} < 1.01,$ for $j = 2, 4,$ where $\bar{E} = (E_2 + E_4)/2$
- $E_j < E_i,$for $i = 1, 3, 5,\ j = 2, 4$

If the above conditions are satisfied, we check if the price crosses the neckline, which is defined as the line through E_2 and E_4. The sell signal (if any) is generated at the first price between $E5$ and $E6$ below the neckline.

Rectangle bottoms are defined as inverted rectangle tops and generate buy signals. Note that in technical analysis handbooks (e. g., Bulkowski (2011) and Kirkpatrick II and Dahlquist (2012)) rectangle tops and bottoms are defined as both reversal and continuation patterns depending on the direction of the breakout, that is, upwards for buy signals and downwards for sell signals. For the analysis, the reversal types are exclusively used in order to restrict this pattern type to generate either buy or sell signals.

To assess the consistency of the calibration of smoothing parameter h and corresponding multipliers,the introduced pattern recognition algorithm is applied with different calibrations. The test procedure runs on the set of daily data (closing prices) in DAX and DAX30 stocks from April 2009 to November 2012 which also will be used in Section 3.5. For this sample and the parameter calibration used for further analyses ($h = 1 + 8\sigma$), I find 529 patterns of which 52.17% are buy signals. Alternative calibrations are $h = 1$ constant, $h = 1.5$ constant, and h determined through cross-validation multiplied by 3. Table 3.3 shows the number of detections for each calibration and pattern type. Larger h-values lead to fewer detected signals, but the set of signals remains relatively consistent, i.e. the signals detected under stronger smoothing are a subset of the signals

TABLE 3.1: **Comparison of Pattern Recognition Calibrations.** This table compares TA signal generated from different calibrations of the smoothing factor h of the Kernel regression. The first block shows the number of patterns from the final smoothing parameter calibration $h = 1+8\sigma$, where σ denotes the return volatility of the respective price window. The second block contains recognition results from h determined by cross-validation with multiplier 3. The third and fourth block show results from constant $h = 1.0$, and $h = 1.5$, respectively. Row (1), (2), and (3) show numbers for the patterns (inverse) head-and-shoulders, double top & bottom, and rectangle top & bottom, respectively. For each calibration the total number of signals as well as the absolute and relative number of signals matching the signals of the final calibration are reported.

	Vola adj. h=1+8σ	Cross-validation h-multiplier=3.0			Constant h=1.0			Constant h=1.5		
			matches			matches			matches	
	# signals	# signals	abs.	rel.	# signals	abs.	rel.	# signals	abs.	rel.
(1)	327	277	160	57.76%	361	281	85.93%	178	127	71.35%
(2)	100	89	58	65.17%	97	92	94.85%	116	77	77.00%
(3)	102	99	49	49.49%	128	96	94.12%	51	43	84.31%

detected under less smoothing. In the presented alternative calibrations the share of signals in accordance to the final calibration is between 49% and 95%.

3.4.3 Intraday Trading Signals

The previous section introduced TA signal definitions and corresponding recognition methods based on daily data. In order to analyze the microstructure of trading, a higher observation frequency is expedient. When it comes to markets such as Xetra, where trading is very intense, a daily observation of TA signals would introduce a high uncertainty with respect to a relation between trading variables (e. g., spreads and turnover) and observed TA signals. Hence, the precise definition of TA signals matters more since already a small deviation of, say, the applied filter bands of a moving average might lead to a substantial time shift of the actual signal trigger. In case of chart patterns, which include a multitude of parameters, this problem might become particularly cumbersome. Since I have no information on the actual calibrations Technical Analysts use for intraday trading, it seems questionable whether chart patterns can be analyzed on an intraday level in a sensible way.

To address these issues, I simplify the employed Technical Analysis strategies and try to keep the definitions as unambiguous as possible. For intraday analyses, an observation frequency of one minute is used. This seems to be a realistic time granularity with respect to Technical Analysis trading because minutely data is typically available in popular trading tools such as Saxo Trader by Saxo Bank and the IB Trader Workstation by Interactive Brokers. Furthermore, one minute should be a sufficient amount of time for a human trader to process new price information, make decisions, and place an order. For technical reasons, i. e., with respect to the statistical analyses conducted in the following sections, minutely data results in a convenient sample size[7] that still allows for complex procedures.

In case of moving averages, I use SMAs of one minute midquote observations calculated over 5, 10, 20 and 50 day periods. A long (short) signal is triggered when the midquote price p_t crosses the average from below (above) and exceeds (undercuts) by at least one minimum tick size, i. e., the conditions for a long signal are $SMA^d_{t-1} > p_{t-1} + ticksize$ and $SMA^d_t < p_t + ticksize$. The conditions for a short signal are defined analogously. Let the indicator variable *SMA long* equal 1 if any of the four SMA triggers a buy signal and, analogously, *SMA short* shall equal 1 if any of the four moving averages triggers a sell signal.

As mentioned above, chart pattern involve a higher fuzziness regarding a precise signal definition that captures trading activities of potential Technical Analysis traders. Thus, chart patterns are not used as defined in Section 3.4.2, but their components, that is, the highs and lows in the price graph. Technical Analysts call these 'significant' (local) lows and highs support and resistance levels[8] (SRL). They interpret a support or resistance level in the price graph as evidence that supply and demand will tend to behave similarly when prices approach this level once more.

In order to detect such levels, I use an adopted version of the approach by Lo et al. (2000) presented above. Based on intraday quote data, I determine support and resistance levels in moving windows consisting of 510 1-minute observations, which

[7] A one year sample of 30 DAX stocks has about 4 million stock-minute observations.

[8] See Kirkpatrick II and Dahlquist (2012, p.230f) for a discussion of support and resistance levels from the perspective of Technical Analysts.

is equivalent to one trading day. In each window, I fit a cubic spline to the midquote price data. Instead of the Kernel regression approach, splines are computationally more efficient to smooth the price series. Due to the immense size of the intraday data and because the algorithm must run over rolling windows for each observation, splines improve the run time drastically. The smoothing parameter of the spline is selected relative to the midquote volatility in the respective window, i. e., smoothing increases when prices are more volatile. This yields a reasonable number of support and resistance levels in calm as well as in very stressed market situations. Let $vola$ denote the hourly midquote return volatility in the respective window. The recognition algorithm works follows:

1. Fit a cubic spline using the annualized midquote return volatility in basis points (bps) as smoothing parameter.
2. Evaluate the spline at each observation.
3. Determine local extrema in the spline series.
4. Determine the positions of the actual highs (lows) by searching the highest (lowest) trade price between two spline lows (highs).
5. A high (low) is valid if its relative size to the previous low (high) is larger (smaller) than $1 + vola$ $(1 - vola)$ or if it is higher (lower) than the previous high (low). In the latter case the previous high(low) is deleted.
6. An extrema is not valid if it appears within the last 60 observations of the window.

This algorithm results in a list of active highs and lows that refers to the last observation within the window. Then the window is moved by one observation and the algorithm is applied again to obtain a new list of highs and lows. Figure 3.3 illustrates the algorithm procedure. In the shown window we find four local maxima (highs) and two local minima (lows) highlighted by circles. Thereof one maximum and one minimum is not valid, hence both are deleted from the list. In case of the maximum this is because of a higher local maximum at a later point of time. In case of the minimum, the current (last) midquote price is lower than the detected local minimum. In the shown example, we obtain a list of three active maxima and one active minimum for the current price (last price in the window).

The existence of active highs and lows does not mean that a support or resistance level is necessarily active. A support level is trigger with respect to the current (bid)

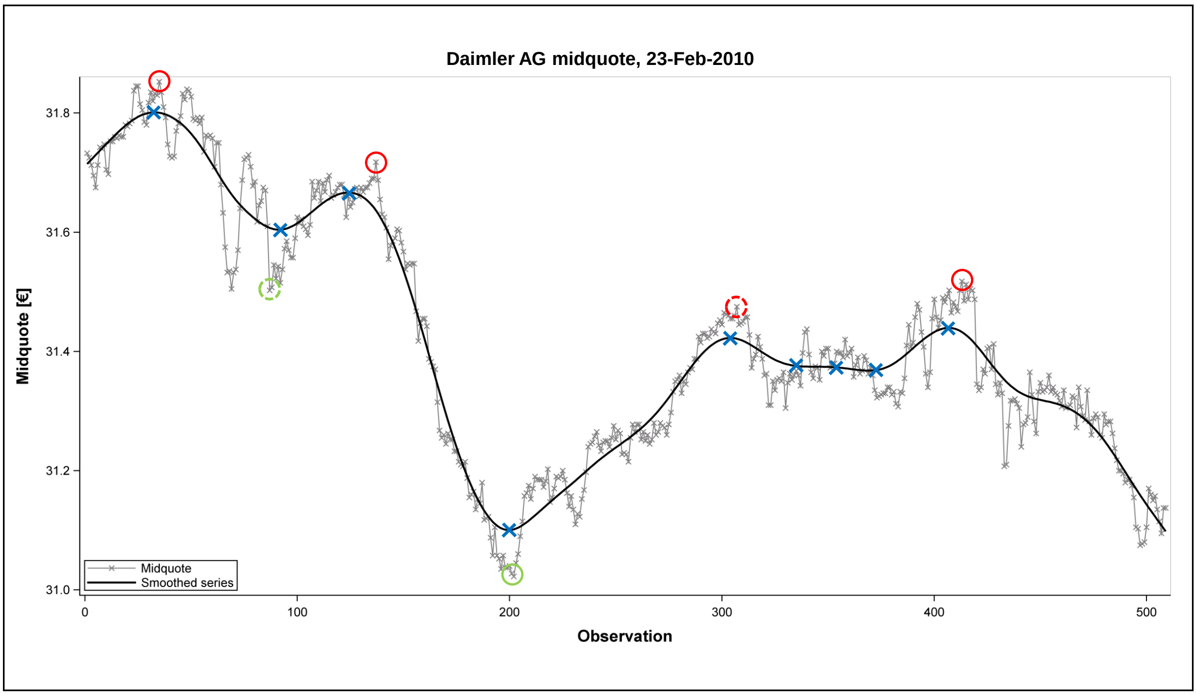

FIGURE 3.3: **Visualization of the Smoothing Algorithm.** This figure shows an example pass of the algorithm used to define support and resistance levels. The observation window consists of 507 midquote prices of Daimler AG on February 23, 2010. The black line shows the smoothed spline output. Crosses on the smoothed spline mark local highs and lows. Encircled midquote prices refer to highs and lows satisfying the minimum distance condition from the previous low and high.

quote when the best bid is within a range of one tick size around a local minimum determined by the above procedure and lowest trade price in the previous 1-minute interval was not below that range. The latter accounts for the situation when a support or resistance level already has been broken, which typically would be noticed by the Technical Analysis trader if she uses candlestick charts. The definition of an active resistance level at the best ask follows analogously.

Since the recognition algorithm just considers observations from one day, the resulting support and resistance levels do only refer to very recent price developments and should be only be relevant (if at all) for trading in the near future. In particularly, for retail investors it seems unlikely that (high-frequent) intraday data is used after weeks or months and over long time periods. In addition, I performed tests including long-term extrema, e. g., weekly and monthly highs and lows. The impact on the results is negligible as the number of occurrences when stocks trade exactly at such price levels is very small.

Within a 6-year sample of 30 DAX stocks the relative appearance of support and resistance levels among all 1-minute observations is 2.1% and 2.3%, respectively. Note that a single level may be active across multiple observations if quoted prices satisfy the defined conditions for several minutes. In comparison, intraday moving average signals trigger more rarely. I find active SMA long or short signals in only about 1.0% of the 1-minute intervals across the sample.

3.5 Retail Investor Trading

This section assesses the relation of retail investor trading and Technical Analysis. In particular, I focus on two popular Technical Analysis techniques: moving averages and chart patterns. Trading data from Stuttgart Stock Exchange provides a promising basis to address Research Question 2 postulated in Section 1.2. I use trading data on the extensively traded product types knock-out warrants and (vanilla) warrants due to their predominately speculative characteristics, which are described in Section 2.1.3. Furthermore the considered products must have the DAX index or its constituents as underlying.

The main idea of the presented approach is to use the algorithmically identified Technical Analysis trading signals in the underlyings and relate them to the trades in associated knock-out products and warrants. Based on this relation, different dimension of retail investor trading are studied, e. g., trading activity , trading performance, and further trade characteristics.

3.5.1 Related Literature and Research Hypotheses

This section outlines TA-related literature with a focus on retail investor trading. For the presented study it plays no crucial role whether Technical Analysis is actually profitable or not. It seems unlikely that the typical retail investor determines the best performing rules and calibrations. Yet she might use Technical Analysis because she believes it is useful for trading or because other successful investor use it. In this respect, behaviorally motivated papers on the usage of Technical Analysis find a high popularity of TA-related methods among professional investors. For instance, Flanegin and Rudd (2005), Menkhoff and Taylor (2007), and Menkhoff (2010) show that fund managers and professional traders believe that Technical Analysis has some relevance in financial markets.

The survey replies from fund managers in Menkhoff (2010) show that for 87% Technical Analysis plays a role in their investment process and for 18% it is the preferred way of information processing. On the other hand, it seems likely that similar considerations are valid for retail investors. First, information and knowledge on Technical Analysis is widely available in textbooks and online resources. Secondly, retail investors could imitate professional investors or experts if they follow their activities, for instance, online blogs, boards, and social trading platforms.

Using a large sample of Dutch discount brokerage clients and a corresponding survey, Hoffmann and Shefrin (2014) find that 32% use Technical Analysis to some extent while for 9% it is the exclusive trading approach. By matching the survey responses to the investor's accounts, they show that Technical Analysis is highly detrimental to the investors' wealth causing a marginal cost of about 50 basis point per month. Furthermore investors using Technical Analysis trade more frequently and hold more concentrated portfolios with higher non-systematic risk exposure. Interestingly, the share of Technical Analysis users is even higher than reported by Lease et al. (1974) in the 1970's which might be due to increased availability of Technical Analysis tools typically provided by financial websites and online brokerages today. Hoffmann and Shefrin (2014) also find that Technical Analysis investors trade lottery-like instruments with right-skewed return distributions, but negative risk-adjusted returns.

Etheber et al. (2014) find intense TA-related trading activities for German retail investors. About 10% of the retail investors in their brokerage dataset trading activities can be consistently related to moving average trading strategies. Overall trading activity of the sample population increases 30% on moving average signal days while earning no abnormal returns.

From a theoretical point of view, Blume et al. (1994) develop a model which shows that market price and volume information can play a role in the learning process of investors. Hence Technical Analysis might have a value for investors who are not fully informed. Ebert and Hilpert (2014) argue that trading based on moving average strategies might be more appealing for retail investors compared to a buy-and-hold strategy if they have prospect theory preferences (cf. Section 2.3). Assuming a typical stock return distribution (e. g., log-normal) applying a moving average strategy on such return series skews returns to the right because extreme losses are avoided at the cost of usually higher transaction fees and a bad performance in sideways markets. The resulting right-skewed (realized) return distribution is more attractive for investors having prospect theory preferences (instead of being risk-neutral mean-variance maximizers).

Hence, the popularity of Technical Analysis might be explained by the fact that it addresses typical behavioral characteristics of retail investors, e. g., prospect theory preferences (Ebert and Hilpert, 2014), demand for gambling and entertainment (Hoffmann and Shefrin, 2013), or the confirmation bias (Friesen et al., 2009). Herding behavior of retail investors could be promoted by the popularity of Technical Analysis in financial media from which investors could obtain similar trading signals. Several authors argue that Technical Analysis has a broad media coverage, e. g., Park and Irwin (2007), Hoffmann and Shefrin (2014), and Avramov et al. (2015). The triggering of TA signals might just generate attention in a particular stock and thereby addresses the search problem of retail investors (Barber et al., 2008) resulting in increased turnover due to an attention effect. Additionally there might be a cascading effect in the sense that if there is a meaningful number of Technical Analysts causing a relevant amount of turnover in that stock, non-TA trader might put their attention on this stock due to the abnormal turnover. The actual relevance of Technical Analysis in financial media (information provider) compared to other forms of information and security analysis tools (e. g., fundamental data, analysts forecasts, corporate news) unfortunately is hard to measure.

Apart from retail investor trading, there are several papers analyzing the effect on the microstructure of stock trading, which is discussed in Section 3.6. However, some of these studies have implications for the study of retail investor trading as well. In particular, Bender et al. (2013) examine head-and-should chart patterns in NYSE and AMEX stocks over a 40 year period of daily data and find excess trading volume on trading signals days as well as narrower (quoted) bid-ask spreads. Etheber (2014) confirms excess trading activity around moving average signals for the German stock market. The latter suggests that retail investors trading on Stuttgart Stock Exchange are also interested in TA-related strategies.

In sum, academic research indicates that Technical Analysis plays a role in security markets and the decision making process of (retail) investors. Based on the presented literature, I derive the following hypotheses regarding Research Question 1a.

Hypothesis 1a:

(i) *Trading activity in speculative (structured) products is abnormally high on TA signal days.*

(ii) *TA buy (sell) signals lead to a positive (negative) net positioning of retail investor trades.*

Irrespective of surging trading activity, characteristics of (round-trip) trades associated with TA signals could be different compared to the overall population of trades. Empirically, trading accounts of retail investor exhibit a bad (return) performance, which is particularly true for trading structured products and other derivatives (cf. Section 2.4). Likely drivers of this under-performance are informational and cognitive shortcomings (cf. Section 2.3). As discussed by Ebert and Hilpert (2014), Technical Analysis techniques can be considered as an algorithmic modification of the realized return distribution. If followed strictly and if transaction costs are ignored the sample of TA-related trades has different characteristics than typical trades by retail investors. Potentially alternated characteristics might be performance, disposition effect (skewness of realized return distributions), leverage and realized volatility. This leads to following hypotheses regarding Research Question 1b.

Hypothesis 1b:

(i) *Trades in accordance with Technical Analysis trading signals earn higher raw returns and risk-adjusted returns.*

(ii) *The realized return distributions of trades which are in accordance to Technical Analysis trading signals are less left-skewed than the realized return distributions of comparable trades.*

Part (i) of the hypothesis rests on the assumption that a systematic approach to trading might lead to favorable trading results. Furthermore, investors who use Technical Analysis might be more engaged with investment strategies in general. A principle often stated in popular Technical Analysis textbooks is the limitation of losses from a trade which would translate into assertion (i) of Hypothesis 1b. The second part of Hypothesis 2b can be interpreted as a weaker propensity of TA-based traders to the disposition effect. In this sense, Technical Analysis could be an effective tool for retail investors to realize a return distribution which is more in accordance with their actual preferences.

3.5.2 Sample Selection and Descriptive Statistics

This section describes the data selection from the databases described in Section 2.2 used within this study. The analysis of retail investor trading behavior bases on leveraged structured products having the DAX index or one of its 30 constituents as underlying. In particular, I use warrants and knock-out products with limited time to maturity for which master and transaction data are available from 04/01/2009 to 12/31/2013. I delete trades in the upper 1 percent turnover and volume quantiles based on each underlying and product class, since these trades are unlikely to be on behalf of retail investors. The selected sample contains 266,783 traded instruments and about 3.7 million trades accounting for EUR 15.2bn turnover in total. Table 3.2 shows the explicit compilation of products and option types. For the analyses in the following sections, I use April 2009 as pre-period and December 2013 as post-period.

TABLE 3.2: **Descriptive Statistics - Trading Data Stuttgart Stock Exchange.** Key facts of trade data from Stuttgart Stock Exchange. The sample contains all trades in DAX and DAX30 warrants and knock-outs from 2009/04/01 to 2013/12/31. The matching rate refers to the share of buy transactions that can be matched by the algorithm described in section 3.5.2. From the resulting sample of round-trip trades, trades below EUR 0.1 or completed in less than two minutes are deleted.

		Knock-Outs		Warrants	
	Overall	Calls	Puts	Calls	Puts
# Instruments	266,783	62,408	47,466	96,827	60,082
# Trades [mn]	3.6950	0.7647	0.9292	1.2330	0.7680
# Buys [mn]	1.9761	0.3753	0.4611	0.6974	0.4424
# Sells [mn]	1.7189	0.3894	0.4681	0.5357	0.3256
Total Turnover [mnEUR]	15.2376	2.1885	2.5711	6.7007	3.7773
Buy Turnover [mnEUR]	7.6444	1.0264	1.2414	3.3844	1.9922
Sell Turnover [mnEUR]	7.5932	1.1621	1.3297	3.3163	1.7851
Avg. Trade Size [EUR]	3,995	2,862	2,767	5,434	4,918
Avg. Time to maturity [d], buys only	129	60	92	234	131
Matching rate	58.1%	72.1%	71.9%	47.8%	49.8%
Round-trip trades [mn]	1.0853				

The post-period is necessary to obtain a reliable matching of buy and sell orders. Since orders are generally anonymous it is not directly possible to infer trading characteristics of completed trades. Thus, I apply a methodology to deduce round-trip trades based on the transaction data sample. As conjectured by market makers of the Stuttgart Stock

Exchange, it is likely that retail investors who buy structured products at Stuttgart Stock Exchange sell there as well. Based on this assumption, I use a matching algorithm to find related buys and sells. Meyer et al. (2014) use a similar algorithm to analyze the trading skill of retail investors.

The algorithm matches buys in an instrument with subsequent sells having the same size and routing information given a first-in, first-out principle. Due to the huge number of instruments there are usually only few trades in each instrument making the trade characteristics quite unambiguous. Thus, the chance of mismatches is relatively low. If no matching sell order is found, I check whether there are sells in the instrument having the same routing information. If this is the case the buy order remains unmatched and is dropped. If not, the algorithm checks whether the product has been knocked-out or has expired and the corresponding final value of the instrument is assigned. Note that knocked-out or expired instruments do not have to be sold by the investor as they are automatically cleared from the trading account by the broker and the issuing bank, respectively. The sell orders considered for matching also include orders which are disregarded due to the filters introduced above.

Overall, 72.0% of knock-out buys and 48.6% of warrant buys can be matched. Most trades are completed within one month. For the final sample, I delete round-trip trades with buy prices below EUR 0.1, trades in the upper 1% volume and turnover quantile, and trades completed in less than two minutes or more than one year. The final matched sample contains 1,085,349 round-trip trades.

TABLE 3.3: **Technical Analysis Trading Signals in DAX and DAX30 Stocks.** Trading signals in DAX and DAX30 stocks from May 2009 to November 2013 (1209 trading days) generated by the technical analysis algorithms introduced in Section 3.4.

Event type	Overall signals	Signals per stock/day	Buy signals	Sell signals
(Inverse) Head-and-Shoulders	327	0.87%	172	155
Double Top & Bottom	100	0.27%	48	52
Rectangle Top & Bottom	102	0.27%	56	46
SMA 200 (0.1% filter)	979	2.61%	499	480
Dual SMA-20-100	522	1.39%	265	257
Dual SMA-50-200	208	0.55%	117	91
Overall	2238	5.97%	1157	1081

To analyze the relation of round-trip trades to Technical Analysis, I focus on signals in the considered underlyings, i. e., DAX and DAX30 stocks. I use moving average and chart pattern signals from the recognition algorithms introduced in Section 3.4.1 and 3.4.2. I use signals from SMAs with 0.1% filters as well as the DSMA-20-100 and DSMA-50-200. All moving average strategies are calculated on the basis of daily observations. Chart pattern signals are considered from head-and-shoulder patterns and its inverse version, Double Tops and Bottoms, and Rectangle Top & Bottom. A detailed description of the definition and calibration is provided in Section 3.4.2. The final set of signals in the 31 considered underlyings contains 529 pattern signals, thereof 52.17% buy signals. Table 3.3 shows detailed numbers on each type of pattern. Depending on the chart pattern type trading signal appear on 0.27% to 2.61% of the 1209 considered trading days.

Finally, a third data set based on the 1-minute intraday data from TRTH is used to calculate returns from the underlying of a product which is used as a benchmark for round-trip trade returns in the trading performance analysis presented in Section 3.5.4.

3.5.3 Trading Activity

Excess Trading Turnover

To capture retail investor trading activity, I use two measures of trading intensity based on the unmatched transaction sample of buys and sells in all considered instruments. Because of the large number of knock-out and warrants from distinct issuers which typically have different product characteristics, I adjust the actual trade turnover for subscription ratio and leverage of the traded product. Otherwise the measure would not reflect the net position size of retail investors, i. e., the funds that would have been necessary to build a position in the underlying containing the same level of risk. Performing additional trading activity analyses with the unadjusted actual turnover yield similar results compared to the adjusted values defined in the following. From the actual turnover TO_{act} of a transaction the leverage-adjusted turnover is derived as

$$TO = \begin{cases} TO_{act} * \left(1 + \frac{R*K}{P}\right), & \text{if call product} \\ TO_{act} * \left(\frac{R*K}{P} - 1\right), & \text{if put product} \end{cases} \tag{3.2}$$

where R and K denote subscription ratio and strike price of the traded instrument and P is the trade price.

The first measure of retail investor trading activity is based on the logarithm of aggregated (adjusted) turnover $TO_t^{(j)}$ of all transactions on day t in underlying j. I replace the 197 stock-day observations having zero turnover by the smallest observation in the respective stock during the sample period in order to reduce the impact of extreme observations and to be able to calculate logarithms. Since even small trades have numerically large turnover values, zero-valued observations would introduce relatively much meaningless variation to the time series which is omitted through the proposed transformation.

In general, a time series of aggregated turnover has specific statistical properties to consider. Turnover is always positive and typically has a right-skewed distribution. Furthermore, turnover time series are auto-correlated and related to stock and market volatility. To account for the above properties of the turnover series, I use a similar approach as Bender et al. (2013) who define excess turnover as the residual of an auto-regressive model. For each underlying j, the following model is applied to obtain the resulting residuals $\{\epsilon_t^{(j)}\}_{t=1,\dots,T}$ as a measure of excess turnover, i. e.,

$$\begin{aligned} \ln(TO_t^{(j)}) = \alpha + \sum_{k=1}^{20} \beta \, \ln(TO_{t-k}^{(j)}) + \sum_{i=0}^{5} \left(\gamma_i \, Range_{t-i}^{(j)} + \delta_i ret_{t-i}^{(j)}\right) \\ + \zeta \, VDAX_t + \eta \, ret_{t,t+10}^{(j)} + \theta t + \epsilon_t^{(j)}, \end{aligned} \tag{3.3}$$

where $Range_t^{(j)}$ is the absolute price range of underlying j on day t, $ret_t^{(j)}$ denotes daily log-returns, $VDAX$ is the DAX volatility index, and $ret_{t,t+10}^{(j)}$ denotes the underlying's log-return over the next 10 day period. Hence this approach removes the trend and the correlation to market and underlying volatility from the turnover series. The resulting measure can be interpreted as the surplus of turnover on a given day that we would not have expected based on the model.

In order to analyze the positioning (long or short) of retail investors in relation to the direction of TA signals, I define a second measure of directional trading activity. The adjustments remain the same as in the first case, but aggregation is performed separately for long and short position, i. e., purchases of calls (long turnover) and purchases of puts (short turnover), respectively.

Sell transactions are excluded from this consideration for the following reasons. First, due to the market structure of structured products and the exclusion of short selling, a product must always be bought before it can be sold. Thus, the initialization of a long or short trade always requires the purchase of a call or a put, respectively. Second, selling a previously bought instrument can have several other reasons (e. g., liquidity needs). Even if traders use Technical Analysis for their trading decision, they might have to close their position because the original TA signal does not work as anticipated, although there is no new opposed signal[9] Third, because it is also possible to sell an instrument on another exchange or directly to the issuer, missing sells could introduce some bias regarding long or short positioning, e. g., investors could prefer selling calls directly to the issuer.

For the directional measure of excess turnover, I use a vector auto-regression (VAR) model as follows. Let $L_t^{(j)}$ the aggregated turnover of knock-out calls and call warrants on underlying j bought on day t and analogously $S_t^{(j)}$ put purchases. Let $X_t^{(j)} = (L_t^{(j)}, S_t^{(j)})^\intercal$ and the VAR equation is defined as

$$\begin{aligned} X_t^{(j)} = \alpha + \sum_{k=1}^{5} \beta \ \ln(\mathrm{X}_{t-k}^{(j)}) + \sum_{i=0}^{5} \Big(\gamma_i \ \mathrm{Range}_{t-i}^{(j)} + \delta_i \mathrm{ret}_{t-i}^{(j)} + \zeta_i \ \mathrm{VDAX}_{t-i} \Big) \\ + \eta \ \mathrm{ret}_{t,t+10}^{(j)} + \theta \, t + \epsilon_t^{(j)}, \end{aligned} \tag{3.4}$$

where the right-hand side variables follow the definitions from equation 3.3 but expanded to two-dimensional vectors with identical entries. The resulting two-dimensional

[9]For instance, I do not consider pattern confirmations or failures like so-called pull-backs in case of head-and-shoulders pattern. Furthermore, I do not check whether a triggered signal is negated which is usually the case when price break the trigger price levels (e. g., the neckline) in the opposite direction (cf. Bulkowski, 2011). In general, trading on chart patterns does not necessarily imply to close a position only when a signal in the opposite direction occurs, but after a given time or a given price target has been reached, for example.

residuals $\epsilon_t^{(j)}$ measure excess long and short turnover and the difference $\delta_t^j = (1, -1) \cdot \epsilon_t^{(j)}$ of its entries constitute the excess turnover imbalance, which will be used to analyze the positioning of retail investors.

Results on Trading Activity

To test Hypothesis 1a, I consider the overall trading activity in warrants and knock-outs at Stuttgart stock exchange measured as excess turnover defined above. In a first step, I compare the average excess volume on TA signal days and non-signal days, as well as on three trading days before and five trading days after a signal appeared.

Figure 3.4 shows the values and differences of (lagged) signal days and non-signal days. The upper plot in Figure 3.4 shows the results for pattern signals and the bottom plot moving average signals. In both cases, there is visual evidence that turnover on signal days is different compared to non-signal days. In case of pattern signals the shown values mean that on signal days there is about 35% more turnover than expected based on model (3.3). For SMA signals the increase is about 11%. Table 3.4 lists the values and shows the results from a Sattertwaith t-test on the difference between signal and no signal days. For both cases, the t-test is only significant on a 0.1% level on days of signal.

The generally smaller impact of SMA signals indicates a preference for patterns over a long-term SMA. However, the rather short trading horizon of (round-trip) in trades structured products could partially explain the higher activity around chart patterns which evolve over shorter periods compared to the considered SMA. The considered chart patterns typically evolve over less than two months. For pattern signals, negative excess turnover is found two days before a pattern signal. Retail investors trading patterns might wait for the triggering signal after the last relevant extremum has emerged.

SMA signals exhibit a reversal in excess volume two days after a signal occurred as well as positive excess turnover 4 days after the signal which is of smaller magnitude than on the signal day, however. This might be a result of the considered SMA which in practice are often applied with slightly shifted trigger conditions or varying filter criteria. Assuming some retail investors are no day traders and trade infrequent, the lagged observation of a TA signal could result in increased excess volume some days after an

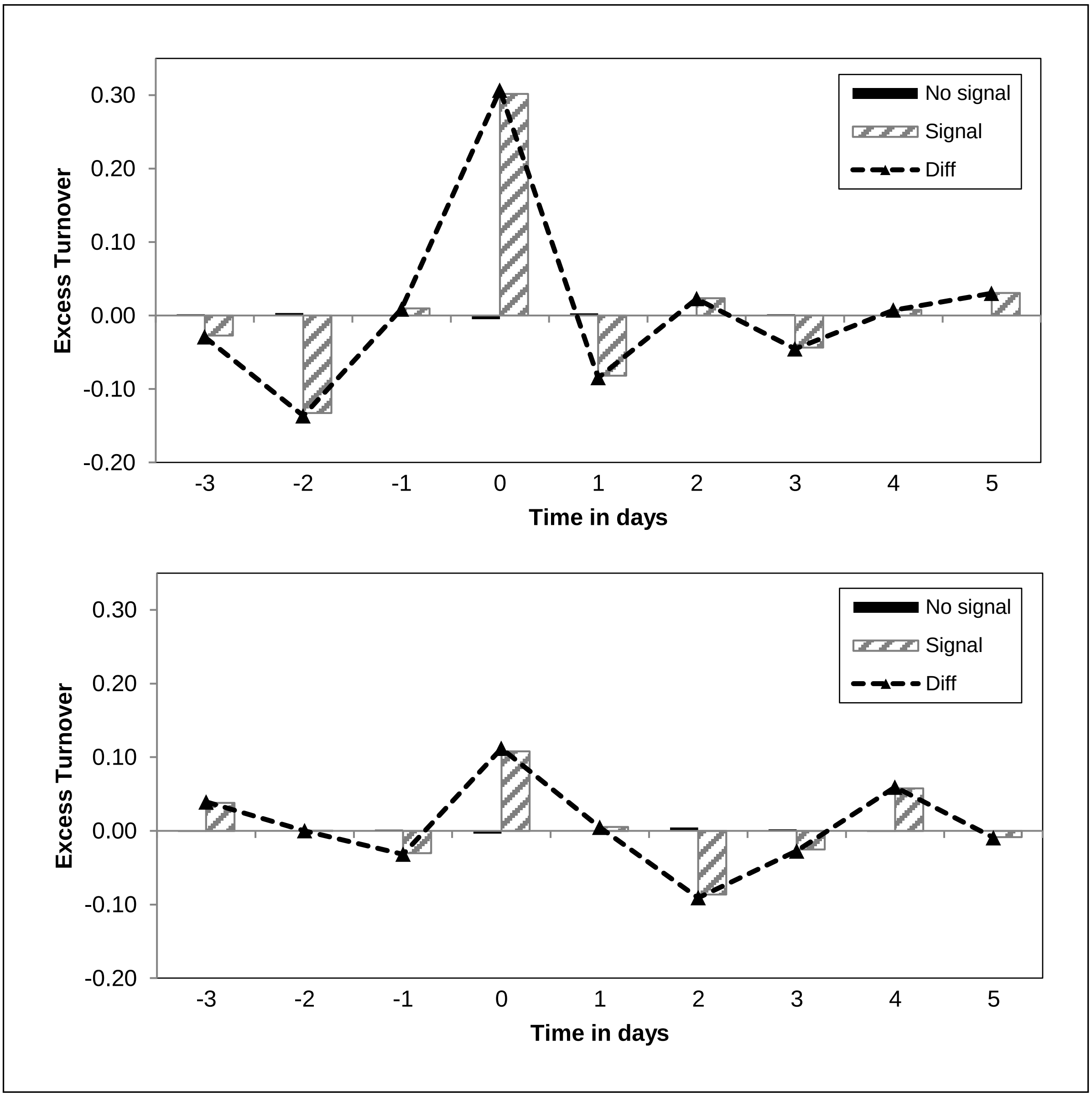

FIGURE 3.4: **Excess Trading on TA Signal Days.** The figure shows average excess turnover in structured products traded at Stuttgart Stock Exchange three days before up to 5 days after a TA signal occurred. The top and bottom plot are based on chart patterns signals and moving average signals, respectively.

event. For example, Lo et al. (2000, p.1719) use a 3-day lag to "control for the fact that in practice we do not observe a realization [...] as soon as it has completed" to account for a potential recognition time. However, the presented descriptive evidence highlight the strongest effect on the signal trigger day, so additional analyses of lagged days is

TABLE 3.4: **Excess Turnover on TA Signal Days.** This tables lists average excess trading activity on signal and non-signal days for different lags. A lag x means some day t for which a signal (or no signal) appears on day $t+x$. The last two columns show t-statistics and p-value from a Sattertwaith t-test on the difference between the signal and no signal groups.

Panel A: Pattern signal					
Lag	No signal	Signal	Diff.	t-stat	p-value
-3	0.0018	-0.0272	-0.0290	-0.63	0.5260
-2	0.0037	-0.1327	-0.1364	-2.50	0.0125
-1	0.0010	0.0098	0.0088	0.18	0.8569
0	-0.0050	0.3018	0.3068	7.19	0.0001
1	0.0031	-0.0816	-0.0847	0.65	0.5175
2	0.0006	0.0236	0.0230	0.15	0.8778
3	0.0019	-0.0435	-0.0454	-0.90	0.3679
4	0.0006	0.0080	0.0074	0.46	0.6430
5	0.0004	0.0307	0.0303	-1.66	0.0982
Panel B: Moving Average Signal					
Lag	No signal	Signal	Diff.	t-stat	p-value
-3	-0.0011	0.0382	0.0393	1.21	0.2253
-2	0.0001	0.0003	0.0002	0.01	0.9946
-1	0.0016	-0.0300	-0.0316	-0.94	0.3499
0	-0.0039	0.1082	0.1121	3.91	0.0001
1	0.0009	0.0056	0.0047	-0.27	0.7883
2	0.0045	-0.0862	-0.0907	1.99	0.0463
3	0.0021	-0.0252	-0.0273	-0.86	0.3925
4	-0.0014	0.0580	0.0594	-2.61	0.0091
5	0.0009	-0.0085	-0.0093	0.14	0.8895

not considered. In practice, retail investors should have the technological prerequisites (e. g., online trading) to react to signals quickly.

A panel regression analysis is used to confirm the descriptive evidence. Therefore, I estimate the following regression for the excess turnover measured as the residuals $\epsilon_t^{(j)}$ obtained from model (3.3).

$$\epsilon_t^{(j)} = \alpha + \beta * Psig_t^{(j)} + \gamma * SMAsig_t^{(j)} + \xi_t^{(j)}, \tag{3.5}$$

where $Psig_t^{(j)}$ and $SMAsig_t^{(j)}$ are dummy variables indicating the occurrence of pattern and SMA signal, respectively, on day t in underlying j. The specification does not include firm dummies since the input excess turnover series was estimated per firm and

TABLE 3.5: **Regression Models of Excess Turnover.** Column (1) presents estimation results from the regression $\epsilon_t^{(j)} = \alpha + \beta * Psig_t^{(j)} + \gamma * SMAsig_t^{(j)} + \xi_t^{(j)}$, where $\epsilon_t^{(j)}$ is the excess turnover in stock j on day t, $Psig_t^{(j)}$and $SMAsig_t^{(j)}$ equal 1 if a TA and MA signal occurred in underlying j on day t or are zero, else. All models use standard errors double clustered on underlying and day. In column (2) the model contains an interaction term of pattern and moving average indicators and for column (3) each pattern and moving average strategy is used as a separate dummy. Standard errors of the coefficient estimates are reported in parentheses. *, **, and *** denote significance on the 10%, 5%, and 1% level, respectively.

	Excess Turnover		
	(1)	(2)	(3)
Intercept	-0.0101*	-0.0103*	-0.0070
	(0.007)	(0.0070)	(0.0070)
Pattern signal	0.3012***	0.3106***	
	(0.0443)	(0.0466)	
MA signal	0.1191***	0.1232***	
	(0.0285)	(0.0286)	
Pattern $*$ MA signal		-0.1937	
		(0.1575)	
Double Top & Bottom			0.2607**
			(0.1291)
Head & Shoulders signal			0.2164***
			(0.0623)
Rectangle Top & Bottom			0.1824
			(0.1497)
SMA200 signal			0.1774***
			(0.0336)
DSMA20/100 signal			0.0329
			(0.0427)
DSMA50/200 signal			0.0080
			(0.0628)
Number of Observations	36301	36301	36301
R-Square	0.0015	0.0016	0.0010

the resulting residuals have zero mean. Consequently the intercept is not significant. However, the variance of the residuals (from (3.3)) could vary between stocks and thus I use Thompson (2011) clustered standard errors which cluster in time (day) and stock as well as in the intersection. Estimation results are shown in Table 3.5, column (1). Confirming the descriptive tests, both signal types have a significant and positive effect on excess turnover in the considered products. Naturally, R-squares are low as most of the explainable variation is already absorbed by the preceding models

(3.3) or (3.4). Furthermore signals are in general a quite rare event – about 6% of all stock-days – and therefore can not explain much of the overall variation. Despite the model confirms the large impact of a triggered trading signal on excess turnover. Extending equation (3.3) by an additional interaction term of SMA and pattern signal indicators the corresponding estimate reported in column (2) shows that this effect is not significant. In general, the intersection is a rare event since only on 36 stock-days a pattern and SMA signal are triggered simultaneously.

An alternative to the two-step approach is to combine models (3.3) and (3.5) in order to estimate the normalization and TA signal effects simultaneously. Although the interpretation regarding the parameters used for the validation of Hypothesis 1a remain unchanged, I prefer the two-step approach as the statistically more sound way to obtain this results. This is basically because we allow the impacts of variables used in model (3.3) to be stock specific and independent of potential effects from TA signals. The estimation results from the full model add no further insights and for this reason are not reported. Furthermore, the two-stage approach is more consistent to analyze the hypothesized effect since it measures the effect with respect to the turnover that would have been expected from contemporaneous and lagged trading variables.

To differentiate between the considered pattern and moving average types, I adapt the regression model by including dummies for each considered pattern and SMA type. Estimation results are reported in Table 3.5, column (3). Double Tops and Bottoms and (Inverse) Head and Shoulder patterns have a large impact on excess turnover and both are statistically significant. The estimated effect of rectangle tops and bottoms is positive but not significant. This could be related to the more ambiguous definition of this pattern type or mean that the pattern is not as popular as the two previous ones. For moving average signals similar results emerge. The SMA200 with 0,1% filters can be associated with a 20% increase in excess turnover which is highly significant on a 0.1% confidence level. However, both crossover SMA types show values close to zero. This might be due to the more subjective implementation of double moving averages. While the 200-day SMA is quite unique, the shorter moving average of the DSMA strategy could be applied with basically any length. This could dilute the time of observation and could also mean that the turnover based on these strategies is distributed over multiple days. I also test DSMA10/100 and DSMA20/200 with very similar regression results. Hence, I drop the dual SMA signals for the remainder of this chapter.

Positioning

With regard to Hypothesis 1b, I consider the excess turnover long-short imbalance obtained from regression (3.4) by applying two regression models similar to model (3.5). The first model includes two dummy variables which equal one if any buy (sell) signal in an underlying occurred on day t. The second model utilizes all long and short signals of Head and Shoulder, Double Top and Bottom, and Rectangle Top & Bottom pattern, as well as the 200-day SMA, i. e., eight signal dummy variables in total. Table 3.6 reports the estimation results. Both models do not support Hypothesis 1b. For the model reported in column (1), estimated coefficients of buy signal and sell signal dummies are not significant and close to zero but the signs are in the expected direction. Results from the second model in column (2) show that neither of the estimates of individual trading signals imply a significant impact on turnover imbalances on a 10 % level. Note that only call buys and put buys are considered, i. e., there are no direct reversal effects from selling positions which could be considered as long or short positioning and thus might affect the model results in any direction.

A possible explanation for the insignificant results on excess turnover imbalances could be that the subgroup of retail investor using Technical Analysis tends to trade opposed to the remaining population of retail investors. Since TA signals always appear after a price movement in the same direction of the signal, i. e., prices increase before a buy signal decrease before a sell signal, contrarian trading usually is opposed to TA-based trading. The fact that the increase in trading activity after a TA signal does not translate into corresponding long-short positioning, makes it more likely that a general attention effect around signals is relevant. As mentioned before, other groups of retail investors might rely on volume, media, or other attention grabbing events to solve their search problem of selecting instruments to trade. In this sense, TA-related trading or reports on TA signals could draw the intention of retail investors on a specific instrument who trade opposed to the signals, however. Overall, Hypothesis 1b is rejected, which means that TA signals cannot reliably predict (net) positioning of retail investors measured by daily excess trading imbalances.

TABLE 3.6: **Long-short Imbalance on TA Signal Days.** This table presents result from the regression $\epsilon_t^{(j)} = \alpha + \beta * Psig_t^{(j)} + \gamma * SMAsig_t^{(j)} + \xi_t^{(j)}$, where $\epsilon_t^{(j)}$ is the excess turnover in stock j on day t, $Psig_t^{(j)}$and $SMAsig_t^{(j)}$ equal 1 if a TA and MA signal occurred in underlying j on day t or are zero, else. Column (1) shows a regression specification using aggregated TA signals. In column (2) each TA signal type is used separately, i. e., a dummy variable indicating a signal is included for each TA strategy. In both regressions stock-day double-clustered standard errors are used. *, **, and *** denote significance on a 10%, 5%, and 1% level, respectively.

	Excess-long short imbalance			
	(1)		(2)	
	Estimate	Std. Error	Estimate	Std. Error
Intercept	-0.0161	0.0119	-0.0164	0.0119
Buy signal	0.1072	0.1193		
Sell signal	-0.0737	0.1301		
Head and shoulders			-0.1162	0.2555
Inv. Head and shoulders			0.3694	0.2964
Double top			0.2334	0.5287
Double bottom			0.0443	0.3116
Rectangle top			-0.3375	0.4019
Rectangle bottom			-0.0173	0.3077
SMA200 long			0.0738	0.4019
SMA200 short			-0.0698	0.3077
Number of observations	36301		36301	
R-Square	0.0001		0.0001	

3.5.4 Trade Characteristics

In this section, I consider trade characteristics of round-trip trades to assess the question whether trades in accordance to TA signals have different properties compared to the sample population. Therefore, I examine matched trades which are obtained through the matching algorithm described in Section 3.5.2.

Performance, Holding Duration, and Leverage

For each round-trip trade i, I calculate three return measures, i.e. log-return r_i, risk-adjusted return r_i^{adj}, and risk-adjusted excess return r_i^{adjex} defined as

$$\begin{aligned} r_i &= 100 * \log\left(\frac{P_{sell}}{P_{buy}}\right) \\ r_i^{adj} &= 100 * \log\left(\frac{P_i^{sell}}{P_i^{buy}}\right) / \left(L * \sigma_i\right)) \\ r_i^{adjex} &= \begin{cases} 100 * \left(\log\left(\frac{P_i^{sell}}{P_i^{buy}}\right) - \log\left(\frac{U_i^{sell}}{U_i^{buy}}\right)\right) / \left(L_i * \sigma_i\right), \text{ for calls} \\ 100 * \left(\log\left(\frac{P_i^{sell}}{P_i^{buy}}\right) + \log\left(\frac{U_i^{sell}}{U_i^{buy}}\right)\right) / \left(L_i * \sigma_i\right), \text{ for puts,} \end{cases} \end{aligned} \tag{3.6}$$

where P^{buy} (P^{sell}) denotes the buying (selling) price, U_i^{buy} (U_i^{sell}) the price of the underlying at purchase (sale), L_i is the leverage of the traded product at purchase as defined in equation (3.2), and σ_i denotes the annualized 20-day volatility of the underlying. Due to the nature of structured products, the selling price is set to 1 cent if a product is knocked-out or to the product's inner value if it expires. The historical volatility accounts for the risk involved in a trade. In the literature realized volatility is often used instead because it relates price deviation during the actual holding period to the realized return. However, the calculation of realized returns over very short holding period behave too erratically.

Figures 3.6 and 3.5 depict the empirical distributions of log-returns, holding period, and leverage based on the whole sample. The high leverage ratio incorporated in the traded instruments highlights the highly speculative character of these trades. Since the population of retail investors is expected to be uninformed (cf. Meyer et al., 2014), the gambling and entertainment aspect probably is a major incentive for trading knock-out and warrants. The holding duration supports the perception of such trades (and products) as short-term bets. The median holding period is less than two days, i.e. most trades are completed within one or two days. Note that the histogram is cut off after 30 days, although the maximum trade duration considered is one year. Generally there are also long-term trades as the mean of about 14 days indicates.

Realized returns appear to be quite devastating for the wealth of retail investors

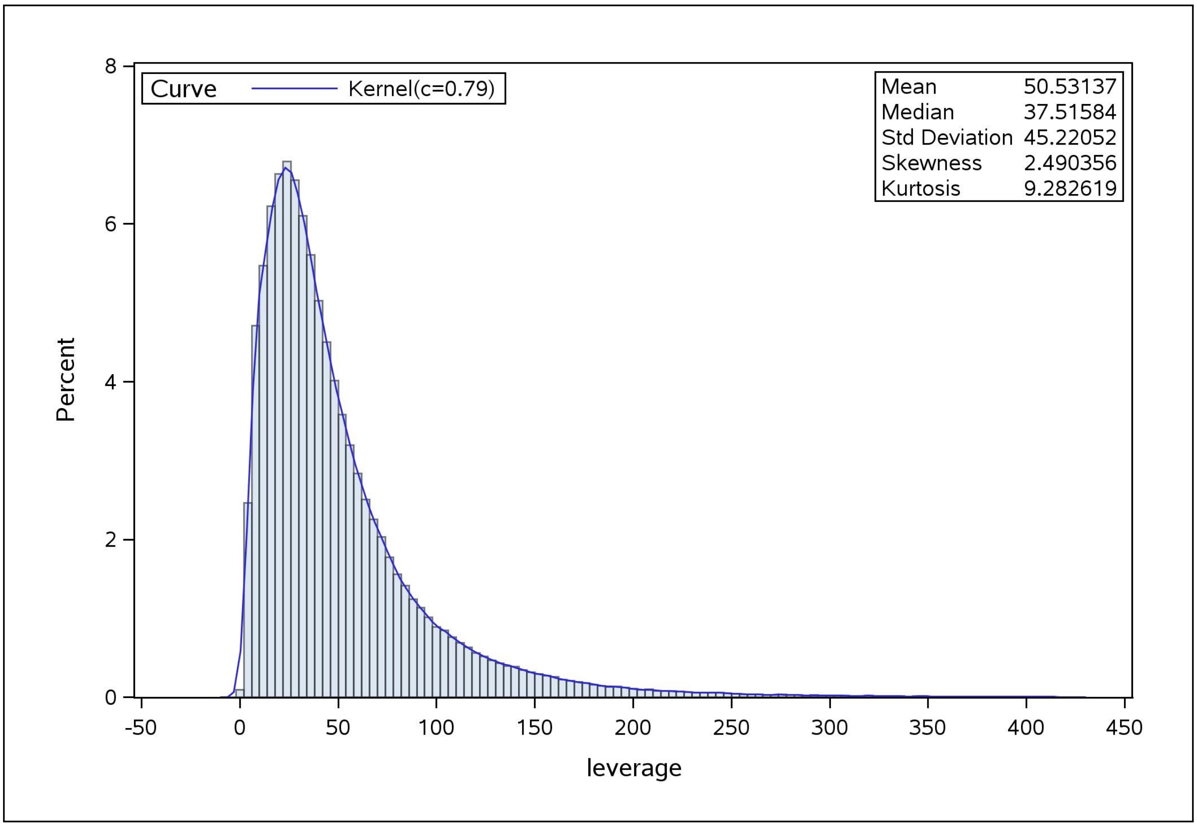

FIGURE 3.5: **Leverage of Round-Trip Trades at Purchase.** The figures shows the distribution of log-returns of round-trip trades in knock-out products and warrants traded at Stuttgart Stock.

trading knock-outs and warrants. On average, a trade loses about 4% of the invested capital. Interestingly, the median log-return is positive, i. e., the log-return distribution is highly skewed to the left. Retail investors realize profits more often, but also realize extreme losses which in many cases means the total invested capital. Approximately 7.48% of the considered trades are knocked-out or expire worthless. Hence the descriptive facts are an indication for the presence of the disposition effect among retail investors trading structured products which confirms several existing studies mentioned in Section 3.5.1).

To assess research question Research Question 1b, I analyze whether there are differences between trades that have been entered on days of a TA signal. Therefore I use trading signals generated by the long and short versions of the three chart pattern types and the SMA200 with 0.1% filters. The dummy variables $buysig_i$ and $sellsig_i$

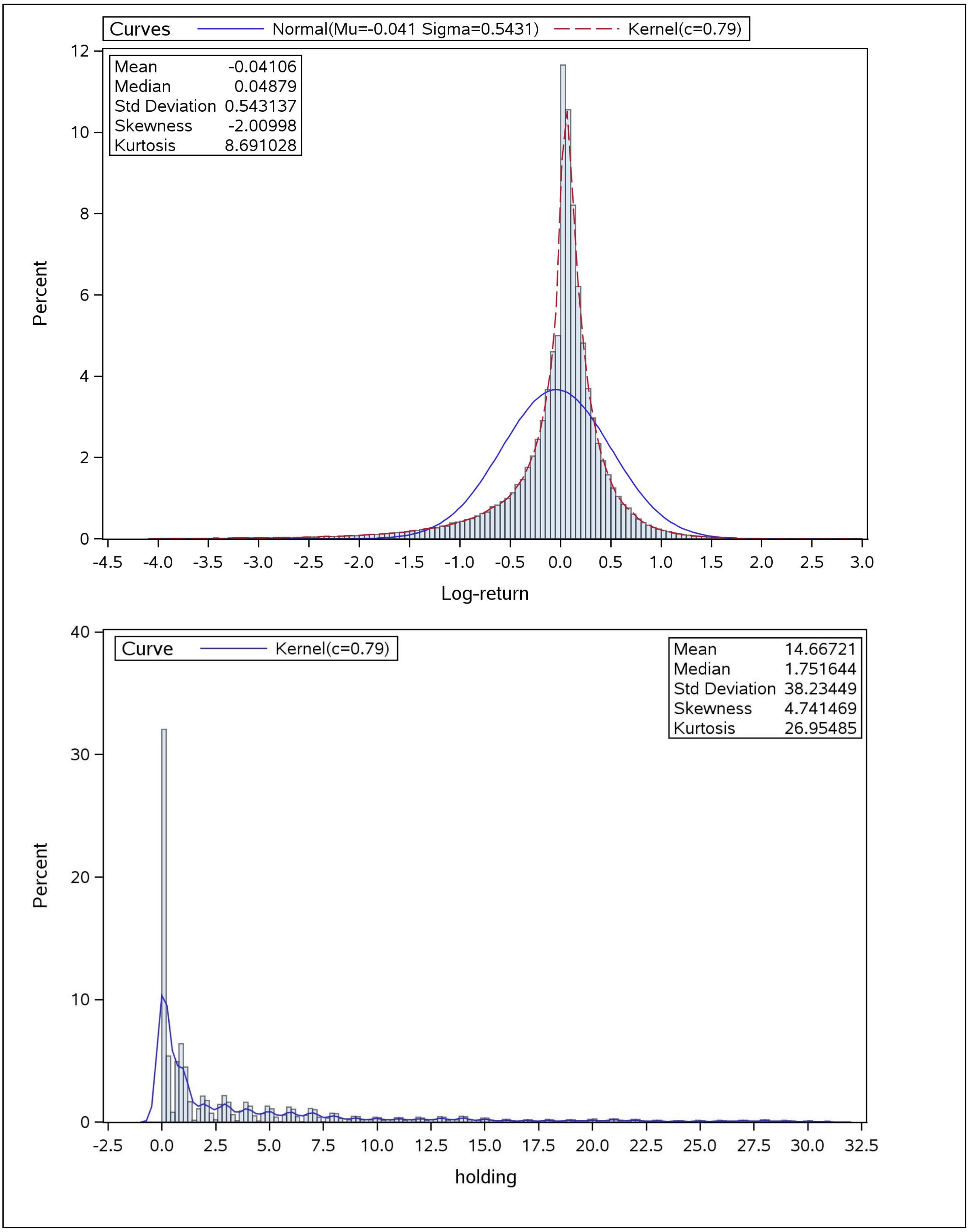

FIGURE 3.6: **Log-returns and Holding Duration of Round-Trip Trades.** The figures shows the distribution of log-returns and holding duration of round-trip trades in knock-out products and warrants traded at Stuttgart Stock. The histogram of holding duration is cut off after 30 days.

TABLE 3.7: **Performance of Round-trip Rrades.** This table presents estimation results from regression model (3.7) defined by $r_i = \beta_1 * buysig_i * c_i + \beta_2 * buysig_i * p_i + \gamma_1 * sellsig_i * c_i + \gamma_2 * sellsig_i * p_i + \delta_1 * holding_i * c_i + \delta_2 * holding_i * p_i + \eta * market_i + \zeta * ko_i + controls + \epsilon_i$, where c_i and p_i are dummy variables for call and put, $holding_i$ denotes the duration of trade i in days, $market_i$ is a dummy for market buy order, and ko_i indicates trades in knock-out products. The term $controls$ is defined as $\sum_j \left(ul_i^{(j)} * c_i + ul_i^{(j)} * p_i \right)$, where dummy $ul_i^{(j)}$ equals 1 if the underlying of $trade_i$ is j. I regress three return measures, i.e. raw log-return, risk-adjusted return, and excess return, which are reported in column (1), (2), and (3), respectively. Standard errors of the coefficient estimates are listed in parentheses. All regressions use standard errors double clustered on underlying and day. *, **, and *** denote significance on a 10%, 5%, and 1% level, respectively.

	Round-trip trade performance		
	Raw log-return	Risk-adjusted return	Risk-adjusted ex. return
Buy signal ∗ call	8.2668***	1.1130***	0.0528***
	(2.7153)	(0.4115)	(0.0284)
Buy signal∗ put	-13.9863***	-1.9780***	-0.0652***
	(1.2242)	(0.2201)	(0.0187)
Sell signal ∗ call	-3.2263***	-0.7176	-0.0096
	(1.2234)	(0.2305)	(0.0203)
Sell signal ∗ put	5.2310***	-1.0733***	-0.0348*
	(0.9175)	(0.2573)	(0.0257)
Holding ∗ call	-0.2450***	-0.0628***	-0.0074***
	(0.0356)	(0.0092)	(0.0025)
Holding ∗ put	-0.6815***	-0.2502***	-0.0151***
	(0.0323)	(0.0114)	(0.0026)
Market order	-0.6821***	-0.1781***	-0.0141***
	(0.2116)	(0.0463)	(0.0049)
Knock-out product	0.8899	-1.1081***	-0.0792***
	(0.7381)	(0.0664)	(0.0254)
Controls	underlying ∗ put, underlying ∗ call	underlying ∗ put, underlying ∗ call	underlying ∗ put, underlying ∗ call
Number of Obs.	1085349	1085349	1085349
R-Square	0.0785	0.1499	0.1188

are defined such that they indicate a triggered buy signal and a sell signal, respectively, on the day round-trip trade i was entered. The following regression model, which employs standard errors double-clustered on underlying and days as proposed by Thompson (2011) and Cameron et al. (2011), analyses potential drivers of round-trip trade returns:

$$\begin{aligned} r_i =& \beta_1 * buysig_i * c_i + \beta_2 * buysig_i * p_i + \gamma_1 * sellsig_i * c_i + \gamma_2 * sellsig_i * p_i \\ &+ \delta_1 * holding_i * c_i + \delta_2 * holding_i * p_i + \eta * market_i + \zeta * ko_i + controls + \epsilon_i, \end{aligned} \tag{3.7}$$

where c_i and p_i are dummy variables for call and put, $holding_i$ denotes the duration of trade i in days, $market_i$ is a dummy for market buy order, and ko_i indicates trades in knock-out products. The term $controls$ is defined as $\sum_j \left(ul_i^{(j)} * c_i + ul_i^{(j)} * p_i\right)$, where dummy $ul_i^{(j)}$ equals 1 if the underlying of $trade_i$ is j and is set to zero otherwise. The latter means that the model includes fixed effects for each underlying and trade direction (i.e. long or short trades) in terms of call or put products. Hence, I evaluate whether trade performance varies within the peer group of products on the same underlying and of the same option type given the assumption of other effects are related across all groups. This specification is necessary because puts and calls on the same underlying generally behave diametrically[10]. Since the expected effects of trading signals on performance are opposed for puts and calls, I use separate dummies for buy signals and sell signals, respectively.

Table 3.7 reports estimation results for the three return measures defined in (3.6). Round-trip trades entered on the trigger day of a TA buy signal in the same direction, i. e., call products, earn higher (raw) log-returns, while put trades earn lower returns (see Table 3.7, column 1). Parameter β_1 and β_2 show that trades in calls earn 8.27% higher log-returns while put trades earn 13.99% lower log-returns. Both estimates are significant on a 1% level. Note that the abnormal returns estimated by the parameter coefficients are with respect to other trades on the same underlying and option type. Therefore such trades must not necessarily have been profitable, but, at least, have been more profitable relative to comparable trades. Analogously, trades entered on sell signal days exhibit a better performance in puts and weaker performance in calls. The estimates indicate an impact on log-returns of 5.23% for puts and -3.23% for calls, thus the effect is slightly smaller than for buy signals but still significant both statistically

[10] In case the underlying price does not change while the underlying volatility increases or time progresses, both, put and call prices could increase or decrease. However, due to the large number of trades and the long observation period such special cases can be neglected here. Alternatively, one could estimate the model for puts and calls separately but then it is not possible to distinguish whether all trades were profitable on buy (sell) signal days or just calls (puts).

and economically.

For risk-adjusted returns, the same effect is present in case of buy signals. The parameter estimates become smaller since dividing by leverage and volatility dampens the return values. If a call trade is entered on a buy signal, there is a positive effect on performance of 1.11% while puts earn 1.97% less. For sell signals the estimates differ from the non-adjusted case. While calls do not earn significantly different risk-adjusted returns compared to the remaining trades, puts even show worse performance than puts on non-signal trades and on the same underlying. This could mean that puts on signal days buy the extra return from increased risk. So results regarding raw returns of puts bought on sell signal days might be driven by some very successful trades which use very high leverage.

For risk-adjusted excess returns results are similar to those of risk-adjusted returns. In this case, estimates are very small as much variation is removed by the standardization. Since the return of a knock-out or warrant is a function of the return of the underlying and the incorporated leverage, the standardized excess return mainly consists of time-dependent and non-linear components of the price and mispricing, which includes product premia and other costs, among others. For the remaining part of the return, effects are close to the risk-adjusted case, i. e., a significant positive (negative) effect for calls (puts) on buy signal days and no effect in case of sell signals.

Other trade characteristics affecting the performance of a round-trip trade turn out to be as expected. A longer holding duration has a negative impact on returns which is primarily due to the inner costs of structured products. Not surprisingly, market orders also imply lower returns since retail investors have to pay the spread. Note that the applied return measures always include spread costs but do not consider exchange fees or other costs. This implies that the impact on investors' wealth is even worse. Spreads are usually fixed by the market maker and issuing bank on a specific level (typically EUR 0.01) and thus can have a major impact on returns, in particular for low-priced products.

If the adjustment for leverage is omitted, there is no significant difference between knock-outs and warrants. In case of risk-adjustment, knock-outs earn higher returns since trades in this product type exhibit less leverage. On the other hand, price changes are more affected by leverage in case of knock-outs compared to warrants. Since the

TABLE 3.8: **Characteristics of Round-trip Trades.** This table shows results from two regression models using (log-) leverage and holding duration as independent variables. The model is defined as $y_i = \beta_1 * buysig_i * c_i + \beta_2 * buysig_i * p_i + \gamma_1 * sellsig_i * c_i + \gamma_2 * sellsig_i * p_i + \eta * market_i + \zeta * ko_i + \delta ul_v ola_i + controls + \epsilon_i$, where c_i and p_i are dummy variables for call and put, $holding_i$ denotes the duration of trade i in days, $market_i$ is a dummy for market buy order, and ko_i indicates trades in knock-out products. In case of holding duration a dummy variable for call products and the leverage at purchase are added to the equation. In case of leverage as independent variable, the term $controls$ is defined as $\sum_j \left(ul_i^{(j)} * c_i + ul_i^{(j)} * p_i \right)$, where dummy $ul_i^{(j)}$ equals 1 if the underlying of $trade_i$ is j. In case of holding duration we only use control dummies per stock. Results for leverage is reported in column (1) and for holding duration in column (2). All regressions use standard errors double clustered on underlying and day. *, **, and *** denote significance on a 10%, 5%, and 1% level, respectively.

	Round-trip trade characteristics			
	Log. leverage		Log. holding duration	
	Estimate	Std. Error	Estimate	Std. Error
Buy signal $*$ call	-0.1077***	0.0405	-0.2158***	0.0181
Buy signal $*$ put	-0.1011***	0.0163	0.3667***	0.0178
Sell signal $*$ call	0.0525***	0.0148	0.1269***	0.0285
Sell signal $*$ put	-0.2644***	0.0178	-0.7433***	0.0527
Call			-0.2063**	0.1076
Log. leverage			-0.8990***	0.0378
Market order	-0.2091***	0.0046	0.2236***	0.0592
Knock-out product	-0.1840***	0.0061	-2.1629***	0.0748
Underlying vola.	-1.6850***	0.3105	-1.8639***	0.3360
Controls	underlying$*$put, underlying$*$call		underlying	
Number of Obs.	1085349		1085349	
R-Square	0.9476		0.3093	

absolute (option) delta of warrants is always smaller than for equivalent barrier options, prices of warrants change less given the leverage of both products is equal.

To check whether differences in realized returns can also be found in other trade characteristics, the leverage at purchase and the holding period of a round-trip trade are considered. I run a regression model similar to (3.7) where only variables that are known at the entry time of a trade are used as independent variables. Thus, terms containing the holding period are not regressed on leverage which is measured at purchase. I also add terms for the underlying volatility. In case of holding duration, the model controls for underlying and uses a single call product dummy instead of one for each underlying. Table 3.8 reports the estimation results.

Higher underlying volatility leads to less leverage in the selected product as the underlying itself tends to be more risky. With respect to TA signals the results confirm the interpretation from model (3.7) of risk-adjusted returns. Call round-trip trades on buy signal days do not incorporate higher leverage – which might have explained the positive effect on performance – but tend to involve less leverage. An analogous interpretation holds in case of puts. That is, in those trades which are in accordance to TA signals, retail investors have chosen less leverage compared to trades on the same underlying and option type on non-signal days.

With regard to the duration until a round-trip trade is completed, call trades initiated on buy signal days and put trades on sell signal days tend to be sold sooner compared to their benchmark group. Although a longer holding period is generally costly due to the inner costs of a structured product, which logically influence the performance of a trade, a favorable (unfavorable) performance of trades influences the holding duration if retail investors are affected by the disposition effect. Since the sample contains no subject-level information, it is impossible to disentangle the inter-dependencies between realized returns and holding duration, i. e., the decision to close a position, which would allow for a straightforward analysis of potential disposition effects in retail investor decisions.

Skewness

In the models discussed above, I consider trading performance of round-trip trades with respect to TA buy and sell signals and the results show that there are differences in the means of the considered groups of trades. To extend the presented evidence on the mean of returns, I explore potential differences in the return distributions. Figure 3.7 shows the demeaned empirical distributions of round-trip trades in calls and puts on signal, and no-signal days, respectively. For the upper plot buy signals are considered and for the bottom plot sell signals, respectively. In case of buy signals, we see empirical distributions of differing shape. Call trades that are in line with TA signals (group 'call, signal') show less extreme and more symmetric returns around the mean in comparison to call trades on non-signal days (group 'call, no signal'). In case of puts the difference is also evident. Put trades entered on buy signal days have a very long left tail and generally more extreme returns compared to put trades on non-buy-signal days.

Two tests assess the differences in the shape and the higher moments of the return distributions. First, a two-sample Kolmogorov-Smirnov test on the standardized (by mean and standard-deviation) return distributions compares call (put) trades on buy (sell) signal days to the other groups. The test results shown in column 3 of Table 3.9 confirm that the considered return distributions are significantly different on a 0.1% level. This means the return distributions have statistically significant differences in their higher moments. I also run Kolmogorov-Smirnov tests on the original and centered distribution, both resulting in rejection of the null in all pairwise comparisons.

Second, I analyze the skewness of realized returns which can be associated to certain preferences and behavioral effects of retail investors. Therefore I calculate the Bowley coefficient s^B and Groeneveld and Meeden (1984) skewness measure s^{GM}. For a random variable X with mean μ_X, median ν_X, and quartiles $Q_i, i = 1, 2, 3$, these measures are defined by

$$\begin{aligned} s^B &= \frac{Q_3 + Q_1 - 2Q_2}{Q_3 - Q_1} \\ s^{GM} &= \frac{\mu_X - \nu_X}{\mathrm{E}|X - \nu_X|} \,. \end{aligned} \tag{3.8}$$

The standard sample skewness calculated as the empirical third moment is not robust in the presence of outliers and fat-tailed distributions, which both is the case in this sample (cf. Groeneveld and Meeden, 1984). To test whether the skewness measures can be statistically distinguished between two sets of round-trip trades, I construct confidence levels based on a sampling procedure because – to the best of my knowledge – there are no applicable non-parametric two-sample tests for differences in skewness.

The sampling procedure works as follows. I pool the observation from both samples and randomly draw two new sets having the same size as the original ones. For the sampled sets I calculate the absolute difference of the skewness measures. I run 100,000 repetitions to obtain the distribution of this difference from which the 0.1% confidence levels can be derived.

Panel A of Table 3.9 shows the results for buy signals while Panel B presents results

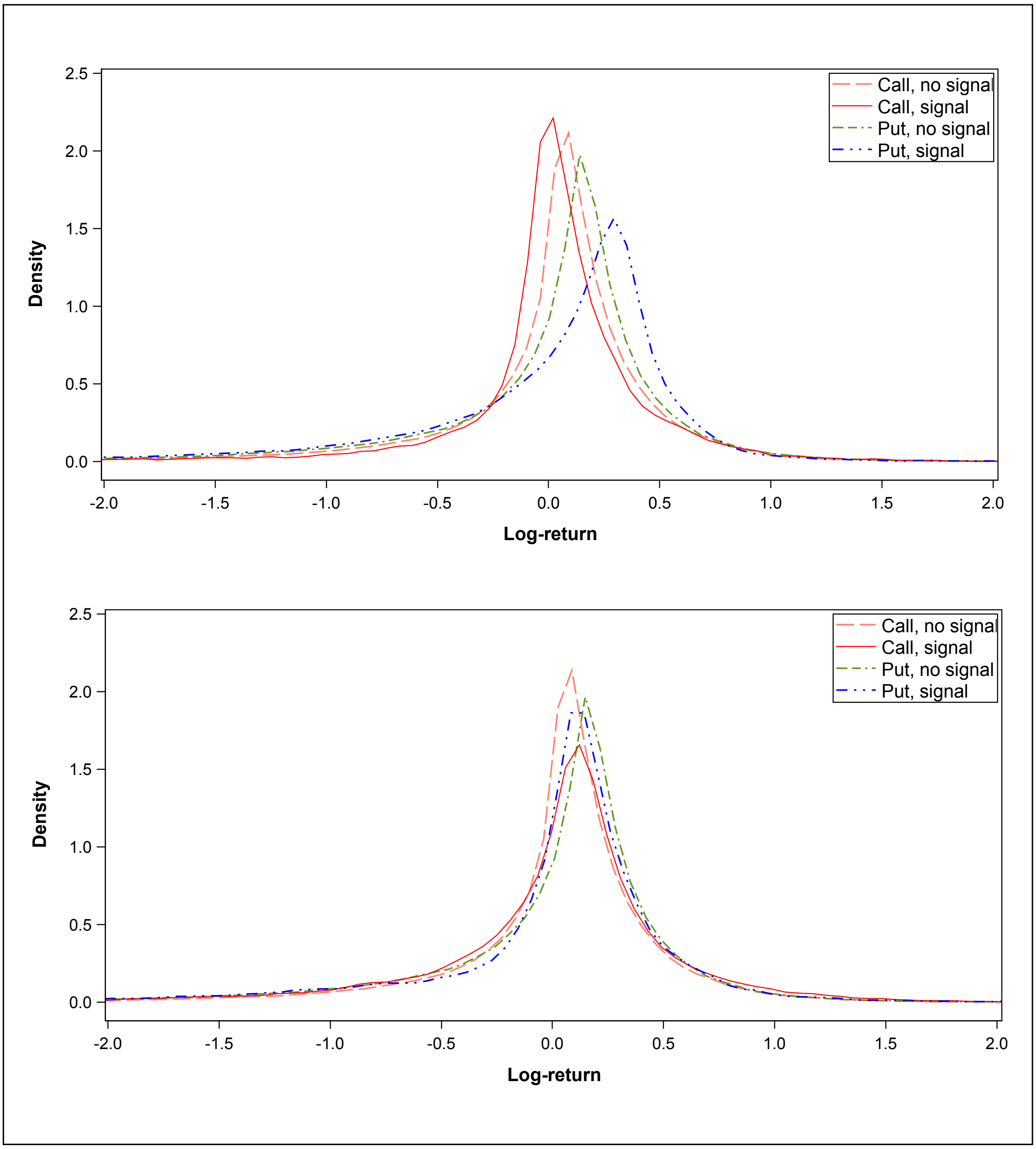

FIGURE 3.7: **Kernel Densities of Realized Log-returns.** The figures show kernel density of the empirical log-return distributions of call and put round-trip trades on signal and non-signal days, respectively. The upper (bottom) plot depicts trades from the classification based on TA buy (sell) signals. In each group the respective mean return is subtracted to improve the comparability between the density graphs.

TABLE 3.9: **Skewness of Realized Returns.** The table reports robust skewness measures of log-return distributions grouped by TA signal events and option type. Panel A reports buy signals and analogues Panel B sell signals. Column 2 and 3 show the Groeneveld-Meeden skewness measure and the Bowley coefficient, respectively. Absolute differences between the call bought on buy signal group and the other groups are validated by bootstrapping from the overall sample (one-sided). 99.9 % confidence internals are reported in parentheses. Column 4 shows two-sample Kolmogorov-Smirnov test statistics and p-value based on the standardized (by mean and standard deviation) empirical return distributions of buy signal call (panel A) and sell signal put group compared to the particular other groups.

Panel A: Buy Signals

		GM skewness		Bowley skewness		Kolmogorov-Smirnov	
	# trades	Estimate	Abs. diff.	Estimate	Abs. diff.	KS statistic	p-value
Signal, Call	9407	-0.1048	-	0.1993	-	-	-
No Signal, Call	564528	-0.2403	0.1356 (0.0444)	-0.0456	0.2449 (0.0606)	0.1115	<0.0001
Signal, Put	16286	-0.4482	0.3434 (0.0470)	-0.3825	0.5819 (0.0648)	0.2080	<0.0001
No Signal, Put	495128	-0.3560	0.2512 (0.0378)	-0.2615	0.4608 (0.0556)	0.1776	<0.0001

Panel B: Sell Signals

		GM skewness		Bowley skewness		Kolmogorov-Smirnov	
	# trades	Estimate	Abs. diff.	Estimate	Abs. diff.	KS statistic	p-value
Signal, Put	8498	-0.3035	-	-0.1092	-	-	-
No Signal, Put	502916	-0.3628	0.0593 (0.0391)	-0.2739	0.1647 (0.0575)	0.0541	<0.0001
Signal, Call	22157	-0.2453	0.0582 (0.0506)	-0.1666	0.0574 (0.0717)	0.0564	<0.0001
No Signal, Call	551778	-0.2374	0.0661 (0.0478)	-0.0363	0.0728 (0.0652)	0.1715	<0.0001

for sell signals. The corresponding confidence levels for the absolute difference of the skewness measures are reported in parentheses. For buy signals (Panel A), the return distribution of calls bought on signal days is less left-skewed ($s^B = -0.1049$, $s^{GM} = 0.1993$) than the return distributions of other groups. In all cases the difference is significant on a 0.1% level. Puts bought on buy signal days, i. e., opposed to trade direction of the TA signal, exhibit the most left-skewed return distribution ($s^B = -0.4482$

and $s^{GM} = -0.3825$). A reason might be that signal triggers are associated with short-term momentum since the signals typically require a preceding price movement in the direction of the signal. The opposite trade could then suffer from this short-term momentum since the high leverage and risk to be knocked-out can quickly lead to an undesirable situation for the investor who might have to sell the position with a big loss. Assuming traders prefer right-skewed returns, then traders who follow TA signals actually achieve this in the present sample. The latter is in accordance to the simulation result of Ebert and Hilpert (2014). The tendency to realize less left-skewed returns indicates that retail investor who use TA-based strategies are less prone to the disposition effect. Using a static rule or another systematic approach might reduce the risk to be influenced by behavioral biases because the decision of closing a trading position is then given by the applied strategy.

For sell signals (Panel B) it turns out that call trades exhibit less left-skewed returns than trades in put products. A reason might be the generally worse performance of round-trip trades in puts which to a large extent is due to the strong market recovery during the observation period. The DAX surged more than 134% (about 19% p.a.) during the sample period of less than five years. Thus, a randomly entered put trade was in most situations an unfavorable bet with a high chance that the investor's position falls below the purchase price. Consequently, these trades are more likely to be negative at some stage and traders who are prone to the disposition effect would be reluctant to realize the loss. Eventually the trade ends up even worse, in particular for knock-out products, since the risk of a total loss rises inevitably and limits the option to wait for a potential recovery in the long-run.

The comparison of put trades entered on sell signal with trades entered on non-signal days shows that the skewness measure significantly different on 0.1% level. For the non-signal group skewness is $s^B = -0.1092$ ($s^{GM} = -0.3035$) and for the signal group $s^B = -0.2739$ ($s^{GM} = -0.3628$). So for both buy and sell signals part (ii) of Hypothesis 1b can be confirmed, i. e., trades in accordance to the respective trading signals are less (left-)skewed than trades in the same direction on non-signal days. In this sense, Technical Analysis traders seem to be more disciplined in their trading and realize losses sooner.

3.5.5 Conclusion

Section 3.5 explores the relation between Technical Analysis and trading on a market dedicated to retail investors. Based on a set of trading signals from typical Technical Analysis techniques, chart patterns and moving averages, I address two research questions regarding the influence of Technical Analysis on trading (cf. Section 3.5.1). How do TA-based strategies and the corresponding trading signals influence trading activity[...] (Research Question 1a) and which are the characteristics of trades that have been initiated in accordance to TA trading signals[...] (Research Question 1b).

With respect to Research Question 1a, I find that overall trading activity is substantially increased on TA signal days. A pattern signal from the three considered pattern types is associated with a 35% increase in excess turnover, on average. Regression results show that Head & Shoulders and Double Tops & Bottoms have a particularly strong impact on market activity. For SMA signals an increase of 11% is observed. This means trading activity in speculative structured products is related to TA signals.

However, the analysis of long-short excess trading imbalances of retail investors exhibits no significant relation between trading signal direction and the positioning of retail investors. This might be due to other attention effects which influence retail investors in their decision making and trading behavior. For example, on an intraday level the increased turnover could initially induce attention and thereby attract more traders who tend to trade in a contrarian way, i. e., opposed to the TA signal. Then, we would find increased excess turnover on this day, but no reliable explanation for the exposure in the direction of the TA signal. Unfortunately, the sparsity of retail investor trading activity in products on a specific stock and the fuzzy observation of TA signals does not allow for a higher time granularity based on the used sample.

Regarding Research Question 1b I find that the trade characteristics of round-trip trades which are initiated in accordance to the direction of TA signals (i.e. long or short) differ from round-trip trades on the same underlying and in the same direction. This supports the view that Technical Analysis changes typical characteristics of retail investors' round-trip trades. In terms of raw returns, trades tend to perform significantly better than comparable trades on non-signal days. Although previous studies show that Technical Analysis – as a systematic trading strategy – is not able to beat the market consistently, people might perform better due to the more systematic trading approach Technical Analysis compared to purely intuitive trading decisions.

Furthermore, I demonstrate that trades in accordance to TA signals have realized a return distribution differing from comparable trades. Round-trip trades in calls on buy signal days, and puts on sell signal days, respectively, are less left-skewed than their peers. By applying a sampling methodology I show that these differences are not merely by chance. This finding indicates a reduced propensity to the disposition effect among the respective group of trades, i. e., losses are realized earlier which results in a more right-skewed return distribution. Further, this result is in-line with the notion that Technical Analysis addresses the gambling aspects of trading and could be used by traders to place their bets. Thereby the simulation evidence of right-skewed return distributions realized from TA strategies (Ebert and Hilpert, 2014) is empirically confirmed.

The presented results are limited with respect to the set of Technical Analysis strategies that I assume to be relevant based on related literature and practice, i. e., articles in financial media, Technical Analysis handbooks, or trading blogs. The calibration of the patterns and MAs is arguably subjective, however the consideration of daily observations should offset some of the fuzziness regarding the exact trigger time of a signal. It is also possible that the relatively narrow set of MAs and the fixed pattern calibration do not include the calibrations retail investors typically use to trade structured products. However, I believe that searching or fitting the Technical Analysis method yielding the highest result would not have been a sensible approach for this study.

The trading data from Stuttgart Stock Exchange allows for an observation of trading on a population level, i. e., no individual trading information is available. Therefore, the observed effects can not consistently be related to a group of traders who actually traded on TA signals and will do so in future. Similar to the approach of Hoffmann and Shefrin (2014) who use a survey to identify the investment style of broker clients, a complementary survey among trading participants could be an interesting extension to shed light on the trading incentives of retail investors trading at Stuttgart Stock Exchange.

Overall, the study indicates a relevant role of Technical Analysis in retail investors trading, so the question arises why people actually use it. Does the use of Technical Analysis and the related trading just entertain investors – hence it had a value in itself – or is the lack of investment knowledge and the demand for a 'guiding system' for making investment decisions a dominant factor? If the latter is true, many offers by brokers and information providers excessively praising chart and Technical Analysis tools should be considered critically. How Technical Analysis, charts, and other related methods influence individual trading decisions of investors remains an important question to be answered in future research.

3.6 Liquidity and Price Discovery on Xetra

The previous section highlights the role of Technical Analysis in retail investor trading on a market for speculative financial products. Hence, the questions arises whether the results also hold for the general stock market, which has a much more important role for the economy than the market of structured products. As the primary market for German stock companies the stock trading segment of Xetra operated by Deutsche Börse has a major role for the German economy. Furthermore, the market design of Xetra is comparable to most other relevant international stock markets making it a promising research object.

For structured products traded at Stuttgart Stock Exchange, Section 3.5 shows an increase in trading activity when Technical Analysis trading signals are triggered. Since the market for structured products essentially is as a dealer market in which prices are exogenously given, the price of some product is (almost) unaffected by the orderflow in the respective product. In contrast, trading on Xetra actually determines the (spot) price of a share. So if Technical Analysis based trading generates a significant amount of order volume, it has a real influence on supply and demand in the traded stock and ultimately could influence the determined price.

As highlighted in Section 3.3, there is little evidence that Technical Analysis is able to predict future price developments and, in this sense, could make prices more informative. Consequently, Technical Analysts are considered to be uninformed noise traders. However, if the induced noise is of relevant size, there might be effects on price efficiency in the sense that prices could temporarily deviate from efficient levels. These deviations could even be persistent as long as potential gains from enforcing efficient prices are smaller than trading costs which naturally set a limit to arbitrage (Bessembinder and Chan, 1998). Whether such deviations around TA signals exist is a central aspect of the study presented in this section.

In the following, I address the overarching Research Question 2. Section 3.6.3 analyzes the relation of Technical Analysis and liquidity, that is:

Research Question 2a. *What is the effect on dimensions of liquidity supply and demand around Technical Analysis trading signals?*

Section 3.6.4 and Section 3.6.5 deal with questions regarding price efficiency and price discovery:

Research Question 2b. *Is there a relation between TA trading signals and measures of informational efficiency, i. e., do price processes show characteristics associated with inefficient prices?*

Research Question 2c. *Given that technical traders are uninformed noise traders, what is the effect on transitory and permanent price components when Technical Analysis trading signals appear?*

Section 3.6.1 presents the existing literature on the relation of Technical Analysis and liquidity from which I develop hypotheses regarding Research Questions 2a, 2b, and 2c. Furthermore, I discuss the noise trading characteristic of Technical Analysis and its implications. Section 3.6.6 provides additional robustness analyses complementing the main result sections. Section 3.6.7 concludes on Research Question 2.

3.6.1 Related Literature and Research Hypotheses

Sections 3.3 and 3.5.1 outlined the academic discourse concerning Technical Analysis with a focus on profitability of related strategies and the role of Technical Analysis for retail investor trading, respectively. The latter motivates to assess the relevance of Technical Analysis for the German stock market where retail investors trading only accounts for a small proportion of the overall trading volume, however. As already mentioned, there is evidence that professional investors such as fund mangers, FX traders, and other institutional investors rely on Technical Analysis to some extent (e.g Cheung et al., 2004; Flanegin and Rudd, 2005; Menkhoff and Taylor, 2007; Menkhoff, 2010; Wang et al., 2012). Naturally, institutional investors are associated with larger trading volume and high sophistication suggesting a greater importance for trading on stock markets like Xetra. Given the assumption that TA-related order flows of relevant size exist, the question arises what impact such order flows have for the microstructure of stock trading.

Following the literature, I assume that Technical Analysis traders are uninformed and tend to herd, i. e., they act as noise traders in the sense of Black (1986) and Shleifer and Summers (1990). "Noise makes trading in financial markets possible", i. e., noise trading activity plays an important role as "with a lot of traders in the market, it now pays for those with information to trade" (Black, 1986, p.529, p.531). In the models by Kyle (1985) and Glosten and Milgrom (1985) noise trading leads to reduced spreads as the adverse selection risks of liquidity supplier decrease. Therefore trading based on Technical Analysis should have a positive effect on market quality. On the other hand, in the model of De Long et al. (1990a) noise trader can have negative effects on price efficiency when arbitrage is limited. They argue that noise trader can limit arbitrage trading when they push prices far from fundamental values because risk-adjusted short-run profits become unattractive for arbitrageurs. Similarly, De Long et al. (1990b) analyze a model in which noise traders pursue positive feedback strategies[11] and rational speculators expect their demand resulting in higher levels of price volatility than fundamentals would justify.

Based on experiments Bloomfield et al. (2009) show that beside having positive effects on liquidity, noise trading can slower the adjustment to new information. Empirically, Foucault et al. (2011) find that retail investor act as noise traders since their trading activity has a positive (increasing) effect on volatility. Among others, Barber et al. (2009) and Han and Kumar (2013) show that stocks with high retail trading activity tend to be overpriced. They also demonstrate that overpricing can be persistent over relatively long time periods. Hence, even if traders (arbitrageurs) certainly know that mispricing exists, it might be painful for them to trade in the opposite direction in case the mispricing is persistent. Obviously, persistent mispricing would mean a substantial impairment of market quality.

Generally speaking, "market quality refers to a market’s ability to meet its dual goals of liquidity and price discovery" (O’Hara and Ye, 2011). Yet the measurement of market quality has various dimensions. Trading activity, depth, trading costs (spreads), and price efficiency measured by volatility ratios and decomposition are standard measures applied in the literature. Chordia et al. (2011) provides an overview on market quality

[11]As mentioned in Section 2.4 and Section 3.3, positive feedback strategies or momentum strategies buy winning stock and sell loosing stocks based on some past period. As such, moving average strategies are similar to positive feedback strategies, since in most cases prices need to increase (decrease) before a buy (sell) signal is triggered.

measures and empirical analysis of market quality trends. Many studies[12] analyze market quality measures with respect to some factors of interest, e. g., changes in market systems and microstructure, trading behavior, specific order flows, changes in legislation. Evidently there are strong inter-dependencies between measures of market quality while there is no accepted model which establishes universally defined links between them. Following the literature, I analyze market quality in a static way by considering variations in each measure isolated.

In fact, there is only little evidence on the relation of Technical Analysis to liquidity and market efficiency. Motivated by the behavioral perspective onto Technical Analysis, Kavajecz and Odders-White (2004) analyze the role of Technical Analysis for liquidity provision in terms of limit order book depth. They focus on moving average strategies and SRL in a sample of NYSE stocks during 1997. Level and location of depth in the analyzed limit order books coincide with SRL and trading signals from dual moving averages. Bender et al. (2013) examine head-and-shoulder chart patterns in NYSE and AMEX stocks over a 40 year period of daily data. On trading signal days they find excess trading volume and narrower (quoted) bid-ask spreads. The decrease in spreads is interpreted as a result of lower adverse selection costs of liquidity supplier due to Technical Analysis traders acting as noise traders.

For German large cap stocks Etheber (2014) finds excess trading activity around moving average trading signals. Controlling for a wide range of stock- and market-related variables, aggregated daily trading volume increases by 15% to 55% on days of buy or sell signals compared to normal levels (depending on moving average type and signal direction). The mentioned studies on Technical Analysis and market liquidity use relatively low measurement frequencies or use relative short sample periods[13]. Especially moving average signals appear quite rarely due to their construction which leads to few events per stock-month, for example. Furthermore, the availability of data, market access and automated trading system – even for retail investors – makes it more likely that signals are recognized and traded very immediate (Schulmeister, 2009). This would make it necessary to consider a more immediate relation between Technical

[12] For example, Chordia et al. (2008), Hendershott et al. (2011), Riordan and Storkenmaier (2012), Riordan et al. (2013), Comerton-Forde and Putninš (2015).

[13] Kavajecz and Odders-White (2004) use snapshots taken every 30 minutes over a period of three months.

Analysis and liquidity. Thus, I focus on contemporaneous effects between TA-related signals and measures of market quality.

Based on the research implications summarized above, I derive hypotheses regrading Research Questions 2a and 2b. Due to their relevance for the central concepts of Technical Analysis and due to related academic literature, I focus on SRL and SMA signals which are defined in Section 3.4.3. Since each type basically leads to different trading recommendations[14], the respective hypotheses can differ. For Research Question 2a, I establish the following hypothesis regarding liquidity demand and supply.

Hypothesis 2a:

(i) *SMA trading signals can be associated with an immediate increase in trading activity,*

(ii) *SRL coincide with levels of excess depth in the limit order book,*

(iii) *around TA signals implicit trading costs measured by quoted and effective spreads are lower.*

The latter is based on the argument that the potential noise trading characteristic of Technical Analysis traders reduce adverse selection risks for liquidity providers allowing them to set quotes more aggressively (Bender et al., 2013). Because there is no empirical evidence of increasing liquidity demand around SRL so far, I stick to the assumption that it primarily drives liquidity supply. Naturally more supply can well lead to rising turnover. Kavajecz and Odders-White (2004) provide evidence for the interpretation as liquidity supplying since depth measures rise even after controlling for turnover, but the effect of support (resistance) levels on buy (sell) side demand is not considered.

The consideration of liquidity naturally leads to the more ambiguous questions regarding price efficiency for which literature suggests that both positive and negative effects are possible. Since trading on SRL could be implemented through market and limit orders, the hypothesis regarding a relation to price changes is quite vague. Assuming clustered limit orders have less influence on prices than (directional) excess liquidity demand, persistent effects on the price process seems to be unlikely in case of SRL.

[14]Moving average strategies are basically trend following, while SRL (as defined in this thesis) indicate reversals.

Hypothesis 2b:

Measures of informational inefficiency rise in the presence of SMA signals, i.e. price process characteristics deviate from random walk properties more intensely.

In the context of this study, I suspect TA signals are short-lived, so potential effects on price efficiency should be temporary as well. Therefore, I use an approach to analyze instantaneous deviations from the efficient price (pricing errors) by decomposing prices into transitory and permanent components, which are used to test the following hypothesis.

Hypothesis 2c:

Price discovery is distorted around TA signals since they are related to larger transitory pricing errors while permanent price components are not affected.

3.6.2 Sample Selection and Descriptive Statistics

The study focuses on the thirty largest German stocks based on the DAX30 index composition at the end of 2013. From the data sets described in Section 2.2 the times and sales data and limit order book depth data are employed. The sample period spans from January 2008 to November 2013.

Based on the times and sales data, the common scope of trade and quote based liquidity proxies are calculated[15], namely quoted (half-) spread, effective spread, realized spread (15 min), and price impact (15min). Based on the order book data I calculate cumulative depth on the first (*Depth1*), first five (*Depth5*) and first ten (*Depth10*) levels, respectively. Analogously, *Depth5Ask* (*Bid*) refers to depth on the respective side exclusively. *AskBalance* (*BidBalance*) is defined as the quotient of the cumulative depth on level 6 to level 10 and the cumulative depth on levels one to five, i. e., $\frac{Depth10-Depth5}{Depth5}$. *Depth5Imbalance*(*Depth10Imbalance*) refers to the ratio of cumulative depth on ask and bid side of the respective levels in the limit order book. To quantify the shape of the depth in the limit order book, *Askmode* (*Bidmode*) is calculated as the distance between the limit price of the order book level with the most shares on the ask (bid) side and the midquote price. Lastly, relative depth calculated for each level on

[15] See Section 2.5 for explicit formulas of the measures applied in this section.

bid and ask side, respectively, that is, $Reldepth_{i,t}(j) = \frac{Depth_{i,t}(j)}{\sum_{k=1}^{10} Depth_{i,t}(k),}$ where $Depth_{i,t}(j)$ denotes the depth (in EUR) on the j-th level in stock i at time t.

To reduce the immense size of the trade, quote, and order book data for further analyses, I aggregate all measures, except $Reldepth$, with respect to 1-minute intervals. An interval begins with every full minute. In the following, an index t of minutely aggregated measures refers to the interval $[t, t+1)$, while in case of atomistic variables (e. g., quoted prices, returns, $Reldepth$) t refers to the observation prevailing at the beginning of these intervals. A 1-minute frequency seems convenient with regard to the recognition of TA signals. First, this frequency should still be practicable by human traders working with charts. Second, a 1-minute frequency results in a level of granularity which mitigates the fuzziness arising from the potentially inexact observation of TA signals by market participants (and by the recognition algorithm), but still is reasonably granular to remain a high precision in the measured variables. In fact, it is an important feature to conduct this study on an intraday level in comparison to existing literature on Technical Analysis and liquidity which has mainly considered lower frequencies. Thereby I intend to identify more immediate relations between the variables of interest.

Within each interval, trade-based measures are weighted by trade volume (in EUR) while quote-based measures are time-weighted, i. e., the weighting factor is determined by the duration a quote observation is active within an 1-minute interval. Intervals during which the daily midday auctions or any other interruption of continuous trading took place are removed. The variable $Range_{i,t}$ is defined as $100 * log(High_{i,t}/Low_{i,t})$, where $High_{i,t}$ and $Low_{i,t}$ refer to the highest and lowest trade price within the interval $(t-1, t]$.

Furthermore, I obtain a set of intraday trading signals by applying the recognition methods for SMA and SRL introduced in Section 3.4.3 to the series of 1-minute midquote prices within the selected sample period. Based on these signal, I define the following indicator variables. $AtSupport_{i,t}$ equals 1 if for stock i the best bid at time t is within a range of one tick size around a local minimum determined by the recognition procedure and the lowest trade price in the previous 1-minute interval $(t-1, t]$ was not below this particular range. The latter accounts for the situation when a support or resistance level already has been broken which can be noticed by the Technical Analysis trader

TABLE 3.10: **Descriptive Statistics.** The table shows descriptive statistics for trade variables of the complete sample of DAX30 stocks from February 2008 to November 2013 used for the regression analyses in this paper. First and last 15 minutes of a trading day are excluded. Quoted (half) spread is calculated as time-weighted average. Effective and realized spreads and price impact are calculated as volume-weighted averages within the 1-minute intervals. All other trade- and quote-based variables in Panel A are expressed as unweighted averages of 1-minute interval measurements across all stocks. Limit order book variables reported in Panel B are calculated as time-weighted averages.

Panel A: Trade-/quote-based variables	Unit	Mean	Std. dev.	Median	IQR
Turnover	1000 EUR	179.8964	363.3769	66.6989	182.0398
Tradesize	1000 EUR	10.6774	13.3164	7.9651	16.3581
Log-return	%	-0.0001	0.0957	0.0000	0.0590
Range	%	0.0705	0.1094	0.0441	0.0950
Quoted Spread	bps	3.9961	4.3318	2.9470	2.2975
Effective Spread	bps	2.9434	3.5350	2.2307	1.9293
Realized Spread, 15min	bps	0.8256	22.6400	0.9747	14.7740
Price Impact, 15min	bps	2.1147	22.5606	1.2431	14.6893
Panel B: Limit order book variables					
Depth5 Ask	1000 EUR	423.0024	496.5318	273.0806	347.1077
Depth5 Bid	1000 EUR	414.2604	474.0321	270.2734	340.7579
Depth5 Imbalance	%	0.6076	22.0254	0.5547	26.5521
Depth10 imbalance	%	0.8617	18.7542	0.7998	21.1708
Askmode	EUR	0.0994	0.2031	0.0600	0.0633
Bidmode	EUR	0.0959	0.1914	0.0598	0.0628
Depthbalance Ask	%	51.9734	12.8503	52.3107	17.5622
Depthbalance Bid	%	51.6436	12.6256	51.8831	17.2527

if she uses candlestick charts, for instance. The dummy variable $AtResistance_{i,t}$ is analogously defined with respect to local highs and ask quotes. Additionally I define the variables $SupActiveL1\text{-}L5_{i,t}$ and $ResActiveL1\text{-}L5_{i,t}$ which signal an active support or resistance level on the first five levels of the limit order book. $SupActiveL6\text{-}L10_{i,t}$ and $ResActiveL6\text{-}L10_{i,t}$ refer to an active support or resistance level on levels 6 to 10 of the limit order book.

As it is standard in the literature, I drop the first and last 15 minutes of each trading day to avoid potential boundary effects on liquidity measures. Table 3.10 shows descriptive statistics for the introduced liquidity measures. The shown statistics are equally weighted across all stocks and 1-minute intervals in the sample. For example, the average turnover in a 1-minute interval is EUR 179,896. The average quoted spread of 4.00 bps is slightly larger then the average effective spread (2.94 bps), which is a known result on Xetra (Riordan and Storkenmaier, 2012) and mostly due to order types providing hidden liquidity and other features of Xetra such as Xetra Midpoint and Xetra BEST (see Section 2.2 for details).

To give an impression on the number of SMA signals and SRL found in the sample, Table 3.11 shows descriptive statistics for the defined TA signal indicator variables. Across all stocks the relative appearance (i. e., the mean of an indicator variable in percent) of SRL in the sample of 1-minute intervals is 2.1% and 2.3%, respectively. Logically the likelihood of finding a support or resistance level that coincides with one of the first five order book levels (level 5 to 10) on the bid or ask side is larger. In comparison, SMA signals trigger more rarely. Long and short signals are active in about 0.5% of the 1-minute intervals across the sample. Yet this should be a sufficiently large number to compare differences in measures in relation to the defined indicator variables given the large sample size.

TABLE 3.11: **Technical Trading Signals.** The table shows the number support and resistance levels determined by the smoothing algorithm described in Section 3.4.3 and moving average signals. Signals within the first and last 15 minutes of each trading day are exlucded. Moving average long and short signals are aggregated for 5-, 10-, 20-, and 50-day simple moving averages applied to minutely midquotes. Support and resistance levels refer to triggered levels, i.e. the current midquote is within the trigger range defined by the respective level. *SupActiveL1-L5* (*ResActiveL1-L5*) and *SupActiveL6-L10* (*ResActiveL1-L10*) indicate that in the respective 1-minute order book snapshot a support (resistance) level is active on the first 5 levels of bid (ask) side and on levels 6 to 10, respectively. Relative appearance refers to the relative number of minutely observations having the respective variable triggered, i.e. the mean of the indicator variables. Mean and standard deviation of the indicator variables are also presented as daily averages, i.e. scaled by the number of 1-minute observations per trading day.

Variable	Rel. Appearance	Mean (per day)	Std. dev.(per day)
Support Levels	2.1104%	10.1088	17.7409
Resistance Levels	2.3369%	11.1936	19.0736
SMA long signals	0.4887%	2.3408	3.3840
SMA short signals	0.4936%	2.3644	3.4098
Sup. ActiveL1-L5	9.0212%	43.2116	122.0634
Res. ActiveL1-L5	9.6584%	46.2638	126.1326
Sup. ActiveL6-L10	11.2505%	53.8900	151.3578
Res. ActiveL6-L10	11.7401%	56.2351	154.1889

3.6.3 Limit Order Book Liquidity

To assess whether Technical Analysis is related to variations in market liquidity on Xetra, I analyze DAX30 stocks along the dimensions trading activity, spreads, and order book depth. Based on the sample of stock-minute observations, I use panel regressions with stock, day, and minute fixed effects (FE) of the type

$$LM_{i,t} = \beta_1 AtSupport_{i,t} + \beta_2 AtResistance_{i,t} + \sum_j TradeVar_j + \sum FE, \qquad (3.9)$$

where $LM_{i,t}$ denotes the respective liquidity measures of stock i at time t, $AtSupport_{i,t}$ and $AtResistance_{i,t}$ indicate active SRL as specified in Section 3.4.3, and $TradeVar_j$ summarize a number of trading related control variables. This includes turnover, market capitalization, (squared) midquote log-return, *Range*, VDAX, and the limit order book measures $Depth1$, $Depth5Ask$, and $Depth5Bid$. Regression models of depth variables additionally include *TickdepthAsk* and *TickdepthBid* which are defined as the number of price levels (ticks) between the first and tenth level of the limit order book, but logically do not include depth variables.

Stock-day fixed effects control for cross-sectional differences not captured by other stock characteristics (e. g., market cap) and non-linear trends which can be observed over time (cf. Section 2.1.1. For example, markets mostly became more liquid during the last decades (Chordia et al., 2011). I use minute fixed effects to control for intraday variation that can be found for stock market liquidity and depth measures (Ahn et al., 2001). Standard errors are clustered by stock. Due to large sample size the feasible complexity of the applied type of standard error and estimation method is somewhat limited. For instance, stock-day double-clustered errors would mean to cluster along approx. 45,000 dimensions which typically leads to memory problems during the computation.

For each variable of interest, I estimate a second model which contains the SMA indicator variables $SMAlong_{i,t}$ and $SMAshort_{i,t}$ instead of the SRL indicators. In the following, I present regression results for the liquidity measures as defined in Section 3.6.2. Section 3.6.6 presents two alternative approaches to strengthen the validity of the results.

Limit Order Book Depth

To analyze liquidity provision in the limit order book, I use an approach similar to Kavajecz and Odders-White (2004). Since I only have data on the first ten bid and ask levels of the limit order book, some measures applied by Kavajecz and Odders-White (2004) cannot be calculated. In particular, depth measures which are calculated in relation to a specific amount of order volume in the book (e. g., x% of the daily average turnover) are less meaningful if only ten levels of the limit order book are known and therefore would result in many missing or boundary values. I employ the measures *Depth5Ask*, *Depth5Bid*, *Depth5Imbalance* and *Depth10Imbalance* as defined in Section 3.6.2 to analyze effects on the amount of depth available in the book. Relative depth (*Reldepth*) and the variables *Askmode* (*Bidmode*) and *ask balance*(*bid balance*) are used to analyze the location of depth in the book to assess whether the shape of the book differs from its typical appearance if TA signals are active.

Table 3.12 shows estimation results for measures based on cumulative depth. Results from model specifications including SRL indicators are reported in Panel A. When the *AtResistance* condition is active cumulated depth on the ask side of the limit order book increases significantly. After controlling for contemporaneous variables, the effect strength indicated by the estimated coefficient means an EUR 252k increase in limit sell order volume on the first five levels of the limit order book. For support levels the estimate is also significantly positive which shows that active support and resistance levels can be associated with periods of generally increased depth. A Wald test on the coefficient differences between support and resistance indicators (F-value 30.81) demonstrates that on the ask side the effect is significantly larger for support than for resistance levels side which supports item (i) of Hypothesis H2a.

Bid side results are accordingly. In this case the estimate means additional 225 kEUR limit buy order volume. The *At Support* indicator coefficient turns out to be larger (Wald test F-value 11.23) than at resistance levels (EUR 170k) supporting the interpretation that depth is increased on both sides of the market but of greater magnitude on the side of the SRL.

Considering depth imbalance ratios between ask and bid side controls for an overall increase in market depth. The regression model of *Depth5Imbalance* employs the

TABLE 3.12: **Depth and Depth Balance Regressions.** This table shows regression results for depth measures regressed on SRL and MA dummy variables as specified in equation (3.9). All depth variables are time-weighted averages over 1-minutes intervals. *Depth5Ask*, *Depth5Bid*, *Depth5*, and *Depth10* denote the Euro-volume on the bid side, ask side, or both sides on the first 5 resp. 10 levels of the limit order book. Depth imbalances are calculated as the net difference between ask and bid depth divided by the total depth on both sides (in percent). *AtResistance* (*AtSupport*) is a dummy variable indicating an active resistance (support) level for the current observation. Analogously, Res.(Sup.) Active L1-L5 (L6-10) indicate an active resistance (support) level on the first five levels (on level 6 to level 10) of the limit order book. All regression specifications contain stock, day, and minute fixed effects and standard errors clustered by stock. *, **, *** denote significance on a 10%, 5%, and 1% level, respectively. Standard errors are reported in parentheses. The sample comprises 30 DAX stock from February 2008 to November 2013.

Panel A: Support & Resistance	Depth5 Ask	Depth5 Bid	Depth5 Imbalance	Depth10 Imbalance
At Support	159.0528***	225.8590***		
	(44.5200)	(55.2319)		
At Resistance	251.5223***	170.4022***		
	(59.9531)	(45.7775)		
Res. Active L1-L5			3.8101***	4.0783***
			(0.3584)	(0.4519)
Sup. Active L1-L5			-3.5971***	-3.9401**
			(0.2625)	(0.3297)
Res. Active L6-L10			0.4171**	2.0809***
			(0.1416)	(0.2304)
Sup. Active L6-L10			-0.6275***	-2.2743***
			(0.1434)	(0.1900)
Quoted Spread	12.4330**	11.5893**	-0.0274	-0.1067***
	(5.7548)	(5.5680)	(0.0179)	(0.0368)
Turnover	0.1035***	0.0822***	0.0004	0.0003**
	(0.0202)	(0.0217)	(0.0002)	(0.0001)
Market cap	-0.3065	-0.3281	0.0052***	0.0044
	(0.5293)	(0.5212)	(0.0047)	(0.0041)
Log-return	12.2034***	-11.2657**	2.8751***	4.6961***
	(4.2384)	(5.2887)	(1.3297)	(1.1476)
VDAX	-14.2867***	-4.6107***	-0.7661***	-0.9957***
	(2.3611)	(0.8359)	(0.1122)	(0.1435)
Range	-209.0537***	-184.4425***	-0.2446	0.0302
	(73.0599)	(65.8218)	(0.3843)	(0.5099)
Tickdepth Bid	-0.2991	-0.2590	-0.0163***	-0.0082
	(0.2455)	(0.2296)	(0.0015)	(0.0086)
Tickdepth Ask	-0.4729	-0.5123	0.0185***	0.0318***
	(0.3753)	(0.3728)	(0.0027)	(0.0066)

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Panel B: *Moving Averages*	Depth5 Ask	Depth5 Bid	Depth5 Imbalance	Depth10 Imbalance
SMA long	-23.6179***	-47.9918***	3.2258***	2.9379***
	(6.3386)	(7.6422)	(0.2268)	(0.3084)
SMA short	-53.6498***	-22.6500***	-3.6154***	-3.3350**
	(9.2880)	(6.7167)	(0.2195)	(0.3242)
Quoted Spread	13.2344**	12.3746**	-0.0284**	-0.1077
	(6.1410)	(5.9269)	(0.0192)	(0.0383)
Turnover	0.1031***	0.0819***	0.0004***	0.0003***
	(0.0202)	(0.0217)	(0.0002)	(0.0001)
Market cap	-0.3163	-0.3388	0.0054	0.0047
	(0.5318)	(0.5237)	(0.0047)	(0.0041)
Log-return	16.9712***	-14.3965**	3.4872	5.5599
	(4.399)	(5.3917)	(1.3295)	(1.1353)
VDAX	-14.9996***	-4.6442***	-0.8794***	-1.1469
	(2.5428)	(0.8817)	(0.1191)	(0.1560)
Range	-217.0744***	-192.2555***	-0.2413***	0.0190***
	(75.0135)	(67.7551)	(0.3926)	(0.5186)
Tickdepth Bid	-0.3101	-0.2685	-0.0174***	-0.0094***
	(0.2546)	(0.2388)	(0.0016)	(0.0089)
Tickdepth Ask	-0.4924	-0.5320	0.0198	0.0332***
	(0.3902)	(0.3871)	(0.0027)	(0.0070)

dummy variables *SupActiveL1-L5* (*ResActiveL1-L5*) and *SupActiveL6-L10*(*ResActiveL6-L10*) to identify active resistance (support) levels on level 1 to 5 and on level 6 to 10, respectively. If a support (resistance) level is active on the first five levels, a significantly positive (negative) shift to the ask (bid) side of about 3.8% (-3.6%) takes place. If a support (resistance) level is present on level 6 to 10 of the limit order book, the estimate is positive (negative) but of much smaller magnitude. This means a support or resistance level is particularly related to depth in close proximity instead to overall depth on the respective side of the order book. The results for *Depth10* imbalance support this view. Here the indicators *SupActiveL6-L10* (*ResActiveL6-L10*) have a more substantial impact of about 2.1% (-2,3%).

If traders submit orders in accordance to a support or resistance level, the increase should already be visible in the limit order book before the best bid or ask price reaches the respective levels. To test this hypothesis, I estimate a model of type (3.9) for each order book level where *Reldepth* serves as independent variable. The model employs dummy variables (*TAlevel1-TAlevel10*) for active support (resistance) levels on the bid (ask) level as regressors and the same control variables as in model (3.9).

TABLE 3.13: **Regression Models of Depth Location Measures.** The table presents regression results for depth location measures regressed on support and resistance level dummies and trading variables as specified in equation (3.9). *Askmode* (*Bidmode*) is defined as the distance (in EUR) between the order book level on the ask (bid) side having the highest depth and the midquote. *Ask*(*Bid*)*balance* is defined as $(Depth10 - Depth5)/Depth10$, where *Depth5* (*Depth10*) is calculated as the cumulated depth (in EUR) on the first 5 (10) levels of the ask (bid) side of the limit order book. *TA-level distance* denotes the distance of the midquote to the nearest resistance (support) level on the ask (bid) side of the limit order book, but only if this TA level is within the range of the reported limit order book levels. *Level1-5*(*6-10*)*Active* indicates an active resistance on the ask side or support level on the bid side on the respective first five levels (on level 6-10) of the limit order book. All regression specifications contain stock, day, and minute fixed effects and standard errors are clustered by stock. *, **, *** denote significance on a 10%, 5%, and 1% level, respectively. Standard errors of the coefficient estimates are reported in parentheses. The sample comprises 30 DAX stock from February 2008 to November 2013.

Panel A: *Support & Resistance*	Askmode	Bidmode	Ask balance	Bid balance
TA-Level distance	0.1825***	0.1817***		
	(0.0390)	(0.0380)		
Level 1-5 active			-1.0612***	-1.2009***
			(0.2373)	(0.2438)
Level 6-10 active			0.6035***	0.4296**
			(0.1708)	(0.1778)
Quoted Spread	0.0021***	0.0040***	-0.1694**	-0.1068
	(0.0006)	(0.0011)	(0.0690)	(0.0645)
Turnover	0.0000***	0.0000**	-0.0014***	-0.0012***
	(0.0000)	(0.0000)	(0.0002)	(0.0002)
Market cap	0.0002**	0.0002**	0.0010	0.0015
	(0.0001)	(0.0001)	(0.0043)	(0.0038)
Log-return	0.0003	-0.0078*	0.4094	-0.4709
	(0.0053)	(0.0044)	(0.5666)	(0.5964)
VDAX	-0.0012**	0.0045	-0.1170***	0.0289
	(0.0006)	(0.0029)	(0.025)	(0.0207)
Range	0.0151	-0.0151	3.6855***	3.3299***
	(0.0098)	(0.0147)	(1.1001)	(0.9929)
Askdepth10	0.0000***	0.0000***	-0.0001***	-0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Biddepth10	0.0000***	0.0000	0.0003	-0.0025***
	(0.0000)	(0.0000)	(0.0003)	(0.0004)
Tickdepth Bid	0.0000	0.0000	-0.0026***	0.0002
	(0.0000)	(0.0000)	(0.0005)	(0.0003)
Tickdepth Ask	0.0003***	0.0022***	0.0061***	-0.0008
	(0.0001)	(0.0003)	(0.0020)	(0.0068)

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Panel B: Moving Averages	Askmode	Bidmode	Ask balance	Bid balance
SMA long	0.0016	0.0037***	-0.1142	0.6301***
	(0.0011)	(0.0010)	(0.1863)	(0.1406)
SMA short	0.0033***	0.0024*	0.6048***	-0.1190
	(0.0012)	(0.0013)	(0.1375)	(0.175)
Quoted Spread	0.0031***	0.0053***	-0.1719**	-0.1117
	(0.0007)	(0.0007)	(0.0699)	(0.0661)
Turnover	0.0000***	0.0000**	-0.0014***	-0.0012***
	(0.0000)	(0.0000)	(0.0002)	(0.0002)
Market cap	0.0003	0.0004	0.0010	0.0015
	(0.0002)	(0.0002)	(0.0043)	(0.0038)
Log-return	0.0048	-0.0106***	0.3700	-0.4108
	(0.0047)	(0.0034)	(0.5652)	(0.6)
VDAX	0.0007*	0.0015	-0.1079***	0.0170
	(0.0004)	(0.001)	(0.025)	(0.0212)
Range	0.0188*	-0.0073	3.6579***	3.3242***
	(0.0094)	(0.0190)	(1.0987)	(0.9954)
Askdepth10	0.0000***	0.0000***	-0.0001***	-0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Biddepth10	0.0000***	0.0000***	0.0002	-0.0024***
	(0.0000)	(0.0000)	(0.0003)	(0.0004)
Tickdepth Bid	0.0000	0.0000***	-0.0026***	0.0001
	(0.0000)	(0.0000)	(0.0005)	(0.0003)
Tickdepth Ask	0.0003***	0.0027***	0.0063***	-0.0010
	(0.0001)	(0.0002)	(0.0020)	(0.0068)

Figure 3.8 illustrates the results for all 20 order book levels. The bottom right panel shows the estimates for regressing order volume on tenth bid level on the ten support level indicators. Each bar represents an estimated TA indicator variable and the error bars correspond to 95% confidence levels. The highest estimate of a bid or ask level is in accordance with an active indicator variable on the same level (e. g., for level 2 on the ask side *TAlevel2* yields the highest estimate). All estimates of *TAlevel* indicator variables are significant except level 8 and level 9 on the bid side. It seems that depth around active support or resistance levels increases most on the first five levels and the effect decreases afterwards. The figure also shows that order book levels close to the SRL are influenced which is similar to the findings of Kavajecz and Odders-White (2004). The imprecise recognition and definition of levels could lead to multiple levels of increased depth. Furthermore, liquidity supplier might undercut price levels of increased depth (e. g., SRL) to increase their execution probability. At best bid and ask (level 1) limit order volume is naturally influenced by liquidity demand which could explain that

effects are less evident than on levels 2 to 5.

I refine the analysis of depth location by measures adopted from Kavajecz and Odders-White (2004) to verify their results for the Xetra sample. This includes the measures *Askmode* (*Bidmode*) and *Askbalance* (*Bidbalance*). For order book mode measures the distance (in EUR) to the nearest support (resistance) level is used as explanatory variable. In order to check whether peaks in depth are in accordance to the SRL only observations with an active support or resistance in the book are considered. Then the variable *TA-level distance* is defined as the distance of the midquote to the nearest resistance (support) level on the ask (bid) side of the limit order book.

Table 3.13 shows the results. For the bid and ask side significantly positive estimates support this relation confirming the results of Kavajecz and Odders-White (2004). Thus, the distance to SRL can be used to identify a location of increased depth in the LOB. The estimated relation between the variables seems to be weaker. An influencing factor in this analysis is the usage of aggregated depth measures (averages) instead of values from snapshots.

Askbalance (*Bidbalance*) measure whether limit order book depth is more concentrated near the best available price or on higher levels of the book and is similar to the 'near depth' measure used by Kavajecz and Odders-White (2004). The negative coefficient estimates indicate that depth on the bid (ask) side of the book is more concentrated on the first five levels if a support (resistance) level is active. Analogously, *Bidbalance* (*Askbalance*) increases when support (resistance) levels are active on the upper levels of the book. In both cases effects are relatively small since coefficients indicate a shift of 0.4% to 1.2% compared to the unconditional standard deviation of *Bidbalance* and *Askbalance* of 12.6% and 12.9%, respectively.

Considering SMA signals, the hypotheses regarding depth and depth location are ambiguous assuming that trading on signals from moving averages mainly influences liquidity demand. If liquidity supplier cannot adjust to the demand quickly, liquidity supply could be adversely effected, which should only effect order book levels close to the best price, however.

I estimate the above regression models using aggregated long and short signals from four SMA strategies. Results for measures of total depth and depth location are

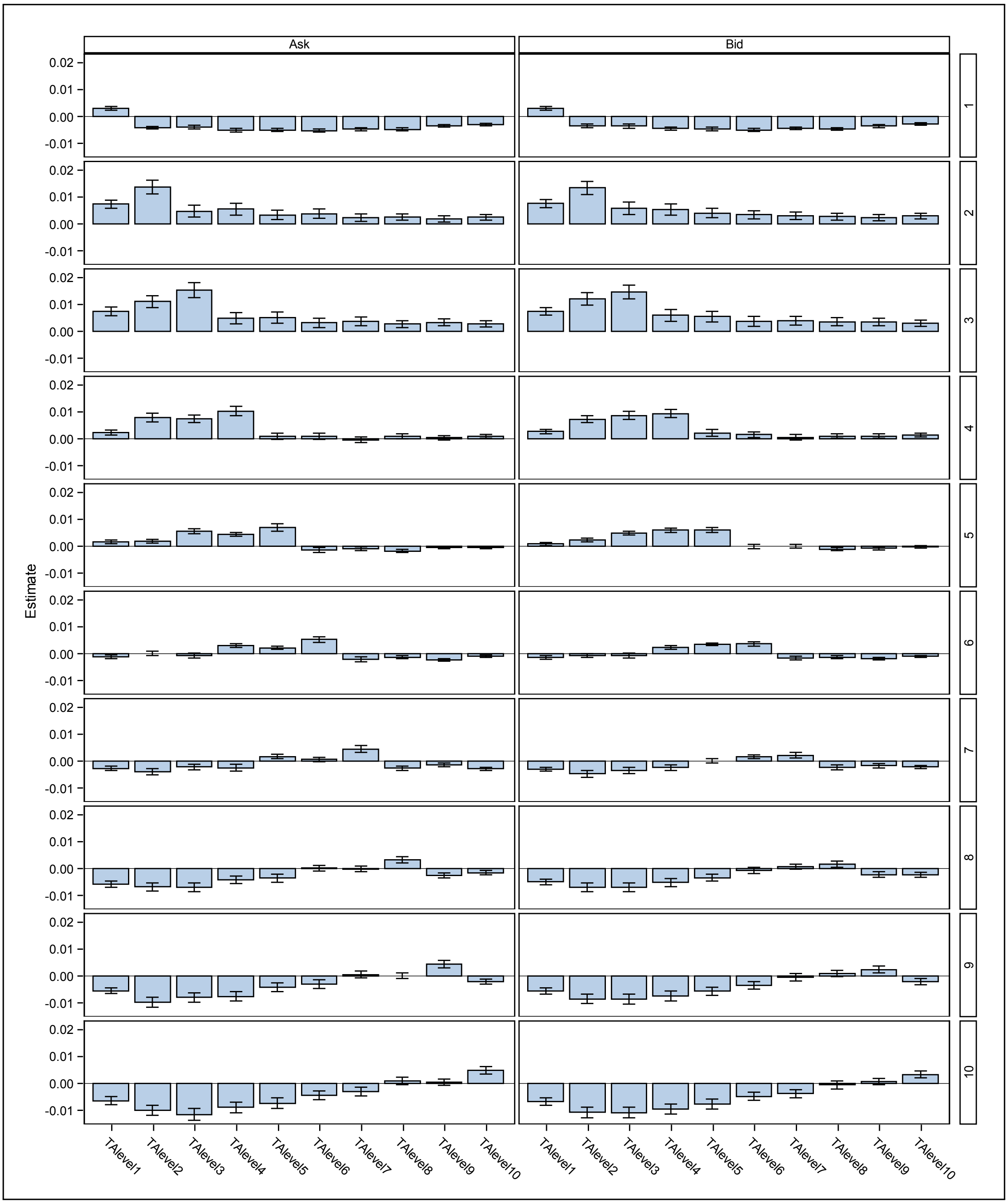

FIGURE 3.8: **Limit Order Book Depth on Support and Resistance Levels.** This figure depicts coefficient estimates of regression models of relative depth on each limit order book level on the ask and bid side. In addition to the dummies signaling active support (resistance) levels on a certain bid (ask) level, the same control variables as in model (3.9) are applied. The regression specifications contain stock, day, and minute fixed effects and standard errors clustered by stock. The drawn bars show the estimated value, error bars refer to 95% confidence intervals.

reported in Panel B of Table 3.12 and Table 3.13, respectively. Cumulative depth on the bid and ask side of the LOB decreases around long and short signals. The estimated effect is stronger for signals in the opposite direction, that is, for *Depth5Ask* in case of short signals and for *Depth5Bid* for long signals, respectively. This seems to be counter-intuitive since we expect liquidity demand in direction of the signal. In fact, limit order supply on one side of the book typically has an inverse U-shape. For example, the execution of one or several levels of the book can lead to an increase of *Depth10* since the succeeding tenth level usually has more depth than the previous best bid or ask.

On the other hand, if the ask moves up (spread widens), traders could adjust their bid accordingly creating a new best bid level which would decrease *Depth10* given the limit order has average size. Although averaging should diminish this effect to some extent, the restriction to a specific number of order book levels is a limitation of the used depth measures and the data sample.

Results regarding depth location measures and SMA signals strengthen the above interpretation. *Askmode* and *Bidmode* increase for signals in opposite direction of the ask side and bid side, respectively, which means depth is located further away from the midquote. The latter is tautological if SMA signals cause midquote changes while order book mode remains unchanged. Controlling for midquote returns might not completely account for this effect since changes in mode are in absolute numbers. Note that the SRL distance variable includes the midquote change as well and thereby accounts for such shifts in the mode measures. Overall, results on depth and depth location indicate no imminent relation between SMA signals and depth in the (higher) levels of the order book. This supports the conjecture that moving average signals primarily drive liquidity demand and thereby affect the state of lower limit order book levels.

Trading Activity and Spread Measures

Table 3.14 shows results from the regression models of turnover, quoted spreads, and effective spreads. Panel A presents results from model specifications containing indicators for active support levels and active resistance levels, respectively. Both coefficient estimates are negative and significant on a 1% level, i. e., trading activity is lower when (best) bid or ask prices are close to a support or resistance level. The coefficients imply an average drop of about EUR 22,000 to EUR 23,000 for intervals with active levels. This is equivalent to approximately 12.5% (6.2%) of the 1-minute average turnover (standard deviation). Although traders who rely on SRL would want to sell (buy) at a resistance (support) level, a particular trade implementation is not directly given. If they believe that (trade) prices reach the respective level limit orders could be preferred to avoid spreads. The results on liquidity supply and demand suggest that the latter case is actually more likely since limit order volume increase and market (marketable) order volume decreases.

TABLE 3.14: **Regression Models for Liquidity Measures.** The table presents estimation results from the panel regressions defined by equation (3.9). Independent variables used to measure market liquidity are turnover, quoted spreads, effective spreads, price impacts and realized spreads (15-minute horizon). Each observation refers to a 1-minute interval over which variables are aggregated per stock. Quote-based measures are calculated as time-weighted averages, trade-based measures as volume-weighted averages. Panel A and Panel B show results for support and resistance levels and moving average trading signals, respectively. All regression specifications contain stock, day, and minute dummies. Standard errors are clustered by stock. *, **, *** denote significance on a 10%, 5%, and 1% level, respectively. Standard errors of the coefficient estimates are reported in parentheses. The sample comprises 30 DAX stock from February 2008 to November 2013.

Panel A: Support & Resistance	Turnover	Quoted Spread	Effective Spread	Price Impact	Realized Spread
At support	-22.1024***	0.6244***	0.4068**	0.1788**	0.2306
	(4.3786)	(0.1883)	(0.1727)	(0.0658)	(0.1402)
At resistance	-23.7086***	0.4814***	0.2992***	0.2027***	0.0976
	(4.4895)	(0.1151)	(0.0951)	(0.0521)	(0.0796)
Turnover		-0.0010***	-0.0012**	0.0003*	-0.0014**
		(0.0002)	(0.0005)	(0.0001)	(0.0006)
Market cap	0.2939	0.0010	0.0012	-0.0004	0.0016**
	(0.2422)	(0.0027)	(0.0015)	(0.0009)	(0.0007)
Squared log-return	-17.3329	3.9208***	0.6154	4.5748***	-3.9584
	(66.0499)	(0.6354)	(1.6952)	(1.106)	(2.5459)
Range	1153.3233***	1.4032	13.2965***	5.4025***	7.8952
	(280.3664)	(1.0166)	(4.7595)	(1.1269)	(5.8595)
VDAX	4.4131***	0.0801***	0.0122	-0.0018	0.0137
	(1.4209)	(0.0128)	(0.022)	(0.0266)	(0.0403)
Depth1	-0.0004	0.0001***	0.0001**	0.0000***	0.0001*
	(0.0006)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Biddepth10	0.0089	0.0000	0.0000	0.0000	0.0000
	(0.0059)	(0.0001)	(0.0001)	(0.0000)	(0.0001)
Askdepth10	0.0259***	0.0000	0.0000	0.0000	0.0000
	(0.0083)	(0.0001)	(0.0001)	(0.0000)	(0.0001)

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Panel B: Moving Averages	Turnover	Quoted Spread	Effective Spread	Price Impact	Realized Spread
SMA long	27.2520***	0.4906***	0.0708	0.0227	0.0492
	(6.0237)	(0.1249)	(0.0819)	(0.0702)	(0.0996)
SMA short	33.1651***	0.5592***	0.0862	0.0769	0.0112
	(6.9841)	(0.144)	(0.0965)	(0.0796)	(0.1253)
Turnover		-0.0010***	-0.0012**	0.0003*	-0.0014**
		(0.0002)	(0.0005)	(0.0001)	(0.0006)
Market cap	0.2946	0.0010	0.0012	-0.0004	0.0015**
	(0.2418)	(0.0027)	(0.0015)	(0.0009)	(0.0007)
Squared log-return	-17.8502	3.9919***	0.6308	4.6624***	-4.0305
	(66.8657)	(0.6418)	(1.7139)	(1.1784)	(2.658)
Range	1153.6798***	1.3572	13.2830***	5.3706***	7.9134
	(280.5307)	(1.0169)	(4.7675)	(1.1499)	(5.8898)
VDAX	4.4271***	0.0805***	0.0124	-0.0018	0.0139
	(1.4262)	(0.0127)	(0.0221)	(0.0267)	(0.0405)
Depth1	-0.0004	0.0001***	0.0001**	0.0000***	0.0001*
	(0.0007)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Biddepth10	0.0086	0.0000	0.0000	0.0000	0.0000
	(0.0059)	(0.0001)	(0.0001)	(0.0000)	(0.0001)
Askdepth10	0.0255***	0.0000	0.0000	0.0000	0.0000
	(0.0083)	(0.0001)	(0.0001)	(0.0000)	(0.0001)

Results for quoted spreads exhibit positive and significant estimates for support levels and resistance levels. At support (resistance) levels quoted spreads broaden about 0.62 bps (0.48 bps). Also effective spreads increase at SRL indicating higher implicit costs for liquidity demander. However, the *AtSupport* coefficient estimate is not significant on a 1% level suggesting the effect is relatively weak. The effect size implies additional costs of EUR 0.32 to EUR 0.43 for liquidity demanding orders of average size (EUR 10,677). So the hypothesis that uninformed trading around TA signals leads to decreasing spread (costs) does not hold in case of SRL (cf. item (iii) of Hypothesis 2a). A reason for increasing spreads might be the imbalance in limit buy and sell orders as the analysis of depth imbalances shows. Excess depth on the side of the SRL could discourage traders on the opposite side to submit aggressive orders as shown by Ranaldo (2004).

To gain insights about adverse selection costs, I analyze the decomposition of effective spreads into realized spreads and price impact with respect to midquotes 15 minutes after a trade. Realized spreads are a proxy for liquidity supplier revenues and the price impact is an approximation of the information content of a trade (Bessembinder and Kaufman, 1997). While I find no significant results for realized spreads, price impacts turn out to be significantly positive at resistance levels. The support level estimate is significant on a 5% level. Despite the noisy estimate, the larger price impacts suggest that marketable orders tend to be more informed. If uninformed traders in the book cause (quoted) prices to be too low, underpricing could be recognized by some market participants who then trade accordingly. In particular at resistance levels, buy orders which are executed against potentially uninformed sell orders on the resistance level could have a stronger impact on the midquote. In Section 3.6.5 I consider the aspect of price discovery and pricing errors in more detail.

Panel B of Table 3.14 reports estimation results for models including SMA indicator variables (*SMAlong* and *SMAshort*). In contrast to SRL, turnover rises significantly after both SMA signal types. After controlling for various trading-related variables, turnover increases about EUR 27,000 (EUR 33,000) for long (short) signals implying 15.1% (18.4%) higher turnover, on average. This finding confirms the daily-based results of Etheber (2014) and corroborates the evidence that an increase on moving average signal days is actually due to trading directly related to such signals.

Similar to SRL, quoted spreads tend to increase significantly. The estimates imply 0.49bps (0.56bps) wider quoted spreads after a long (short) signal occurred. Interestingly, the increase in quoted spreads is not accompanied by a significant increase in effective spreads. Liquidity provider might be encouraged to offer hidden liquidity inside the spread since liquidity provision becomes more lucrative in case of wider quoted spreads or BEST executors execute their order flow at better price than current quotes. If they expect that the additional order flow around SMA signals is more likely to be uninformed, providing additional liquidity inside the spread becomes less risky with respect to persistent adverse price changes. The insignificant effect of SMA signals on price impacts supports this view. Consequently, I find no changes in liquidity supplier revenues measured by realized spreads.

In summary, the results on liquidity measures around SMA signals do not support the hypothesis of decreasing quoted spreads which would indicate reduced adverse selection risks as shown by Bender et al. (2013) for head-and-shoulder chart patterns. Furthermore, I find no significant effect on effective spreads which contradicts item (iii) of Hypothesis 2a.

Because the considered TA signals give a directional trading recommendation, I conduct separate analyses of realized spreads and price impact for liquidity demanding buy orders and sell orders, respectively. In that case the measurement of realized spreads does not readily translate into liquidity supplier revenues, since liquidity supplying strategies typically require trading on both sides of the market. Realized spreads of buys and sells traded at the best bid and ask consist of the (half) quoted spread and the subsequent price move which always is in favor of either the buy or the sell order. Thus, comparing realized spreads of buys versus sells means to compare the future price development after these trades plus average spread costs which might be better for buys or sells depending on trade size and timing. By averaging, price effects on buys and sells do offset in the standard calculation of realized spreads as long as there is no buy-sell-imbalance and no systematic timing advantage of either buys or sells during the considered interval. After splitting buys and sells, the measure basically states how well the execution of specific order types performed over the considered time horizon including spread costs.

Similarly, price impacts are less meaningful as in most cases either buys or sells tend to have a positive impact depending on the sign of the return. In this regard, price impacts of buys and sells basically measure raw returns of a trade over a given horizon (e. g., 15 minutes) excluding implicit costs.

Table 3.15, Panel A (Panel B) shows results for model specification of type (3.9) including SRL (SMA signal) indicator variables. In all four cases, realized spreads increase (decrease) when trades are in the same direction as the TA signals and vice versa for trades in the opposite direction. All coefficient estimates of TA signal dummies are significant on a 1% level. For example, market buys after a SMA long signals tend to have about 1.07 bps higher realized spreads or, in terms of price impacts, midquote prices tend to be about 0.88 bps lower over a 15-minute horizon, on average.

In case of SMA signals, the associated short term directional liquidity pressure could move the price and afterwards it takes some time until liquidity recovers and quoted prices return to the previous levels. The mechanism could be similar to cascade effects of stop-orders causing liquidity pressure when they are highly clustered at some price level. For example, Osler (2003) shows that clustered stop-loss orders in the FX market lead to fast short-term price movements. An empirical study from 2005 mentions that 5% of the liquidity demand on Xetra is due to stop-orders (Prix et al., 2007). Similarly, increased depth on SRL might cause quoted prices to be too high or too low such that market orders in the same direction obtain an inferior price resulting in unfavorable short-run returns. Additionally, I perform the analysis with a 5-minute horizon, which qualitatively yields the same results but smaller coefficient estimates. Although the shown evidence provides no encompassing profitability analysis for the considered TA signal, liquidity demanding orders in direction of a TA signal seem to have inferior short-run performance than comparable trades. This implies that costs of demanding liquidity are relatively high when trading on TA signals.

TABLE 3.15: **Realized Spreads and Price Impacts of Buy and Sell Orders.** The table presents estimation results from the panel regressions defined by equation (3.9). Realized spreads and price impacts are calculated with respect to midquotes 15 minutes after a trade. The measures are aggregated separately for liquidity demanding buy and sell orders over each stock-minute interval. The four regression specifications contain stock, day, and minute dummies. Panels A and Panel B show results for support and resistance levels and moving average trading signals, respectively. Standard errors are clustered by stock. *, **, *** denote significance on a 10%, 5%, and 1% level, respectively. Standard errors of the coefficient estimates are reported in parentheses. The sample comprises 30 DAX stock from February 2008 to November 2013.

Panel A: Support & Resistance	Buy Orders		Sell Orders	
	Realized Spread	Price Impact	Realized Spread	Price Impact
At support	1.8548***	-1.4630***	-1.4294***	1.7554***
	(0.2744)	(0.1870)	(0.1658)	(0.1920)
At resistance	-1.2158***	1.4495***	1.4430***	-1.1509***
	(0.1419)	(0.1671)	(0.1924)	(0.1329)
Turnover	-0.0007***	0.0001	-0.0011***	0.0003**
	(0.0002)	(0.0001)	(0.0002)	(0.0001)
Market cap	0.0025	-0.0014	0.0004	0.0006
	(0.0016)	(0.0009)	(0.0011)	(0.0006)
Midquote log-return	3.4087***	-3.2709***	-3.2457***	2.9887***
	(0.2896)	(0.2839)	(0.2414)	(0.2424)
Range	4.5022***	1.9344***	9.7901***	-1.0126*
	(1.4211)	(0.6221)	(0.8656)	(0.4954)
VDAX	-5.5358***	5.5801***	5.5595***	-5.5304***
	(0.3053)	(0.3058)	(0.3057)	(0.3054)
Depth1	0.0001*	0.0000***	0.0001**	0.0000*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Biddepth10	-0.0003**	0.0003***	0.0003***	-0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Askdepth10	0.0004***	-0.0005***	-0.0004***	0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)

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Panel B: Moving Averages	Buy Orders		Sell Orders	
	Realized Spread	Price Impact	Realized Spread	Price Impact
SMA long	1.0726***	-0.8820***	-1.0529***	1.1413***
	(0.1538)	(0.1418)	(0.1428)	(0.1462)
SMA short	-1.1905***	1.3090***	1.2731***	-1.0813***
	(0.1332)	(0.1303)	(0.1401)	(0.1248)
Turnover	-0.0007***	0.0001	-0.0011***	0.0003**
	(0.0002)	(0.0001)	(0.0002)	(0.0001)
Market cap	0.0025	-0.0014	0.0004	0.0006
	(0.0016)	(0.0009)	(0.0011)	(0.0006)
Midquote log-return	3.3348***	-3.1999***	-3.1726***	2.9171***
	(0.2876)	(0.2825)	(0.2399)	(0.2407)
Range	4.4995***	1.9294***	9.7810***	-1.0105*
	(1.4216)	(0.6227)	(0.8625)	(0.4950)
VDAX	-5.5250***	5.5697***	5.5493***	-5.5203***
	(0.3047)	(0.3053)	(0.3052)	(0.305)
Depth1	0.0001*	0.0000***	0.0001**	0.0000*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Biddepth10	-0.0002**	0.0003***	0.0003***	-0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Askdepth10	0.0004***	-0.0004***	-0.0003***	0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)

3.6.4 Informational Efficiency

The previous section shows that TA signals can be associated with changes in liquidity supply and trading activity. The increase in limit order book depth around SRL and the spiking turnover after SMA signals trigger suggest that price process characteristics could be affected. Since the considered signals recommend to trade in a specific direction prices could be pushed from efficient levels. Even if prices return to their fundamental value, volatility could increase or impounding of other information could be distorted given the directional liquidity shock was sufficiently large. To assess whether prices show characteristics associated with informational inefficiencies, i. e., prices deviate from random walks or become (partly) predictable, I follow the approach by Comerton-Forde and Putninš (2015) and use three typical measures which are calculated on a stock-day basis.

The first measure is based on serial autocorrelations of midquote returns calculated over 10-, 30- and 60-second intervals (cf. Hendershott and Jones, 2005). Both positive and negative autocorrelation in midquotes indicate inefficiencies, for example when new information is priced in slowly or prices tend to overshoot due to liquidity demand. Thus the absolute value of autocorrelation can be used as a measure of informational inefficiency. Since empirical autocorrelation is typically a noisy measure, aggregating autocorrelation over three frequencies results in a less volatile measure (Comerton-Forde and Putninš, 2015). The single aggregated measure is obtained as the first principle component from a principal component analysis applied to the three absolute autocorrelation series. The reasoning behind using the first principal component of the different autocorrelation horizons is to reduce measurement error in each series. Based on the assumption that the measurement error for each series is correlated, the first principal component explains the maximal amount of common variance of the actual inefficiency, but is less noisy than a simple average of the inputs. In order to make the measure comparable, it is scaled to range from 0 (highly efficient) to 100 (highly inefficient).

The second measure is based on ratios of midquote return variances defined by

$$VarianceRatio_{kl} = \left| \frac{\sigma_{kl}^2}{k\sigma_l^2} - 1 \right|,$$

where σ_k^2 and σ_l^2 denotes the k-second and kl-second midquote return variance, respectively, which are calculated per stock-day. If midquote returns follow a random walk then variance should be (close to) time-scaling. Thus non-zero values of the above ratio signal a deviation from the random walk property. As above, the three measures are aggregated by taking the first principal component and then are scaled to range from 0 to 100.

Third, the degree of predictability of stock returns by past market returns measures inefficiencies in the adjustment of stock prices to new market-wide information, i. e., information is incorporated with delay (cf. Hou and Moskowitz, 2005). The basic idea is to run the following two regressions per stock-day.

$$\begin{aligned} &\text{Regression 1:} \quad r_{i,t} = \alpha_i + \beta_0 r_{M,t} \quad \text{and} \\ &\text{Regression 2:} \quad r_{i,t} = \alpha_i + \sum_{j=0}^{10} \beta_j r_{M,t-j}, \end{aligned}$$

where $r_{i,t}$ denotes 1-minute midquote return of stock i at time t and $r_{M,t}$ denotes the 1-minute return of the DAX30 index (market return). I calculate the R-squares of both regressions and define the delay measure as

$$Delay = 100 * \left(1 - \frac{R^2_{(1)}}{R^2_{(2)}}\right).$$

If lagged market returns cannot explain any of the stock's return variability then $R^2_{(2)}$ should be close to $R^2_{(1)}$ and the delay becomes zero indicating a high informational efficiency. Contrary, if much variability can be explained by past market returns, $R^2_{(2)}$ will be larger than $R^2_{(1)}$ and delay increases.

To assess whether informational efficiency alters when TA-based signals are triggered on a trading day, I relate the above measures to the TA-based trading signals as defined in Section 3.6.2. If TA-based trading has an effect on the degree of informational inefficiency, the effect should be increasing in the number of signals on a given day. Since informational efficiency measures are calculated on a daily basis and would be little meaningful when calculated on more granular intervals, I accumulate the intraday SRL indicators *AtSupport* and *AtResistance*, *ResActiveL1-L5* and *SupActiveL1-L5*, as well as *SMAlong* and *SMAshort*. Instances where a support and a resistance level are active in the same 1-minute interval are not double counted. The resulting variables are called *AtSRL*, *LOB_SRL*, and *SMAsignals*, respectively. From the resulting stock-day panel I estimate the following type of regression model, where $IM_{i,t}$ denotes one of the three informational efficiency measures for stock i on day t and $TAcount_{i,t}$ denotes one of the daily accumulated TA indicator variables. The regression equation is defined as

$$IM_{i,t} = \beta \; TAcount_{i,t} + \sum_{j=1}^{6} \delta_j Control^{(j)}_{i,t} + \sum FE, \tag{3.10}$$

where $Control^{(j)}$ include volatility of midquote returns, market capitalization, turnover, as well as time-weighted averages of quoted spread, Depth1, and Depth10, respectively. The regression contains fixed effects for stock and day, standard errors are clustered by stock. I estimate the above model for each informational efficiency measures and TA count variable.

TABLE 3.16: **Regression Models of Informational Efficiency Measures.** This table shows regressions results using three informational efficiency measures based on midquote autocorrelation, variance ratios, and delay to index price movements, respectively. For each measure, three different models are reported. The model in column (1) includes the number of intervals when support and resistance are active at the best bid or ask (*At SR-level*). Analogously, the model reported in column (2) uses a variable for active support and resistance levels on best five levels of the limit order book (*LOB SR-levels*) aggregated per stock-day. Column (3) the number of SMA events during a stock-day (*SMA signals*) is applied. The set of control variables are the same throughout all models and include daily 1-minute midquote return volatility, market capitalization, aggregated turnover, as well as time-weighted average quoted spread, depth1, and depth10. All models include stock and day fixed effects and standard errors double clustered by stock and day. Standard errors of the coefficient estimates are reported in parentheses. *, **, *** denote significance on a 10%, 5%, and 1% level, respectively.

	Autocorrelation			Variance Ratios			Delay		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
At SR-level	0.0019			-0.0106			0.0102		
	(0.0065)			(0.0083)			(0.013)		
LOB SR-level		0.0056**			0.0003			0.0288***	
		(0.0022)			(0.0051)			(0.0089)	
SMA signals			0.0307**			0.0251***			0.2209***
			(0.0128)			(0.0091)			(0.0606)
Volatility	0.0035***	0.0038***	0.0035***	0.0074***	0.0075***	0.0075***	0.0044**	0.0061***	0.0043**
	(0.0008)	(0.0008)	(0.0008)	(0.0017)	(0.0016)	(0.0017)	(0.0017)	(0.0015)	(0.0017)
Market Cap.	-0.0034	-0.0030	-0.0035	-0.0012	-0.0010	-0.0011	0.0164	0.0187	0.0163
	(0.0025)	(0.0025)	(0.0025)	(0.0038)	(0.0037)	(0.0038)	(0.0237)	(0.0246)	(0.0236)
Avg. Quoted Spread	0.1330*	0.0604	0.1383*	0.1263	0.1021	0.1080	3.1029***	2.7324***	3.1220***
	(0.0711	(0.0703)	(0.0708)	(0.2367	(0.203)	(0.2394)	(0.2704	(0.2736)	(0.2682)
Turnover	0.0064**	0.0067***	0.0065***	0.0140***	0.0143***	0.0144***	0.0136**	0.0154***	0.0133**
	(0.0024)	(0.0024)	(0.0023)	(0.0037)	(0.0038)	(0.0037)	(0.0058)	(0.0054)	(0.0058)
Avg. Depth1	0.0000**	0.0000**	0.0000**	0.0000	0.0000	0.0000	-0.0003***	-0.0003***	-0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)
Avg. Depth10	0.0000	-0.0002	0.0000	0.0004	0.0003	0.0003	-0.0006	-0.0012	-0.0005
	(0.0002)	(0.0002)	(0.0002)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0008)	(0.0007)

Table 3.16 shows the estimation results for all specifications of (3.10). The autocorrelation measure is not significantly affected by the variable *AtSRL*. In case of the number of SRL in the limit order book (*LOB_SRL*) and the number of SMA signals coefficient estimates are positive but only significant on a 5% level indicating that the effect is relatively weak and noisy. Considering the effects of trading variables on the measure, volatility and turnover exhibit a significantly positive relation to the autocorrelation measure. Although high trading activity is usually considered as positive for liquidity, high directional liquidity demand, e. g., due to herding behavior of investors, could induce short-term autocorrelation in stock prices (Barber et al., 2009).

The analysis of variance ratios yields similar results. The coefficient for *SMA signals* is positive and significant while the null for both support and resistance variables can not be rejected. With respect to the average number of daily SMA signals, the estimated coefficient (0.0268) means an increase of about 0.95% of the measure's standard deviation. Since SMA signals appear rarely and are short-lived, the potential impact on total fluctuations in informational efficiency measured by variance ratios is very limited in general.

For the delay measure a positive and significant estimate appears for *LOB_SRL* and *SMAsignals*. The coefficient estimate translates into a 5.33% standard deviations increase in the delay measure when an average number of SMA signals are trigger on a trading day. Assuming that SMA trading signals cause temporary (uninformed) directional liquidity demand which is unrelated to fundamental (market-wide) information, stock prices would lag the index price for this short period of time and have to revert afterwards becoming predicable with respect to lagged index price movements. Given that SMA strategies usually[16] need a price movement in the same direction to be triggered, exogenous market-wide events like central bank announcements could temporarily cause high market-wide volatility and at the same time trigger the directional SMA signal resulting in the shown regression result. The consideration of news in order to control for fundamental information events would be out of the scope of this analysis, however.

[16]In general it is possible that a SMA long signal is triggered even if stock prices decrease, for instance when an observations with a relatively high price is dropping out of the SMA calculation and, thus, the average decreases more than the last price.

Summarizing, a relation between informational efficiency and SMA signals exists, but is hardly present for SRL. While SRL increase liquidity provision in the book, which theoretically should support efficient price movement to some degree, the directional liquidity demand associated with moving averages could result in the opposite. The fact that considering SRL on the first five levels of the limit order book (which is a superset of the variable *AtSRL*) leads to stronger effects might be due to liquidity supply clustering on support and resistance price levels instead of levels close to the best bid and ask thereby influencing price discovery in front of the SRL.

Furthermore, the effects on informational efficiency stemming from SRL are partially explained through the relation to other liquidity dimensions like quoted spreads, for instance. As analyzed by Anderson et al. (2013), high-frequency autocorrelation measures are driven by partial price adjustments and overshooting which might be caused by excessive trading around SMA signals. Using low-frequency measures of informational efficiency (e. g., monthly measurement based on daily observations), which principally are correlated with high-frequency measures (Rösch et al., 2013), seems not to be expedient to analyze the relation to intraday TA signals. The statistically significant effect in case of SMA signals indicates that there is a relation to price characteristics associated with inefficient prices. The small effect size reflects the rare and short-living appearance of TA signals, which should restrict the potential impact on a macroscopic measure. Overall, the increase in informational inefficiency is of limited scope.

3.6.5 Price Discovery

State Space Model of Midquote Prices

The previous sections provide evidence that trading around TA signals alters in terms of liquidity supply and demand (e. g., limit order book depth and turnover) and informational efficiency is influenced by some of the signals under consideration. For the latter, the analysis based on global measures of informational efficiency is limited and provides little insight regarding short-term price formation when TA signals occur.

Therefore, I apply a state space model(SSM) of midquote prices to analyze permanent and transitory price changes and volatility in relation to the TA signals selected in Section 3.6.2. Since TA traders are assumed to be uninformed noise traders who potentially trade on the same side of the market, I expect price effects to be increasingly transitory around TA signals. To decompose prices into transitory and permanent parts, I use an adopted approach of the SSM methodology[17] introduced by Menkveld et al. (2007) in the context of market microstructure. Further applications of the state-space approach in the context of price decomposition are, among others, Menkveld (2013), Brogaard et al. (2014), and Hendershott and Menkveld (2014).

The mentioned papers vary in the formulation of the efficient and transitory price components (e. g., inclusion of more lags, trends, exogenous variables) depending on the goal of the analyses. Furthermore, the observations frequency varies from tick (event) time, or equally-spaced intraday observations to daily observations. In contrast to the literature, I do not incorporate treatment variables (e. g., TA signals) into the component equations. First, a pure indicator variable would not be sensible in the price process with respect to the hypothesized effect. Secondly, unlike net order flows or inventory positions of some group of market participants the virtually hypothetical TA signals are more likely to be exogenous to the price discovery process compared to real order flows.

The basic state space model is defined as follows. The observed (log-) midquote price $p_{i,t}$ for stock i at time t is modeled as

$$p_{i,t} = m_{i,t} + s_{i,t}, \tag{3.11}$$

where $m_{i,t}$ is the unobservable efficient price and $s_{i,t}$ the transitory price component (pricing error). The efficient price shall follow a random walk

$$m_{i,t} = m_{i,t-1} + \eta_{i,t}, \tag{3.12}$$

where $\eta_{i,t}$ is a normally distributed error term with zero-mean and variance σ^2_η. Following Brogaard et al. (2014) and Hendershott and Menkveld (2014), pricing errors are modeled as an auto-regressive process, i. e.,

$$s_{i,t} = \phi s_{i,t-1} + \epsilon_{i,t}, \tag{3.13}$$

where $\epsilon_{i,t}$ is a Gaussian error term independent of η with zero mean and variance σ^2_ϵ.

[17] Durbin and Koopman (2001) provide a comprehensive introduction to state space models.

The three model parameters ϕ, σ_η, and σ_ϵ are estimated from 1-minute (log-) midquote observations per stock-day. To fit the model, I optimize the diffuse likelihood function based on the (augmented) Kalman filter output (cf. Durbin and Koopman, 2001, Sec. 7.2), where the initial conditions of the unknown variables are assumed to have infinite variance (so-called diffuse initial values). The transitory error term variance parameter is restricted to 90% of the unconditional variance of $p_{i,t}$ (cf. Brogaard et al., 2014). The auto-correlation parameter ϕ is allowed to take values between ±0.9 in order to avoid non-stationary boundary solutions (see Hendershott and Menkveld, 2014, p.421f, for further discussions). I use the double dogleg optimization algorithm, which yields a high convergence rate (over 99.9%) while being computationally efficient for large samples. Stock-days on which the algorithm does not converge are not considered for further analyses. The unobserved efficient price, which is part of the state vector in the SSM connotation, is obtained through the Kalman smoother by using the (final) Kalman filtering output in a backwards recursion. The smoothing output is used to determine all components of the model given the full sample, i. e., I obtain estimates for the efficient price and pricing error.

The smoothed state variables (efficient price and pricing error) are used to determine the instantaneous level of noise at a point of time. Therefore I calculate the following ratios based on pricing error transitory innovation defined as

$$PEratio_{i,t} = \frac{|s_{i,t}|}{|s_{i,t}| + |\eta_{i,t}|} \quad \text{and} \quad TIratio_{i,t} = \frac{|\epsilon_{i,t}|}{|\epsilon_{i,t}| + |\eta_{i,t}|}. \tag{3.14}$$

Relating the pricing error (pricing error innovation) to the permanent innovation measures the share of the transitory part (noise) compared to total price fluctuation.

SSM Estimation Results

Panel A of Table 3.17 shows descriptive statistics of the estimated SSM parameters across stock-days. The transitory price component (pricing) error is positively auto-correlated ($\bar{\phi} = 0.3766$), on average. Innovation volatility estimates of $\bar{\sigma_\eta} = 7.35$bps and $\bar{\sigma_\epsilon} = 2.03$bps yield an average decomposition of stock volatility (unconditional cross-sectional average 9.57 bps) into permanent and transitory volatility. Note that the conditional volatility is not directly comparable to the sum of the two components since the model parameters are derived from the maximum likelihood function such that the realization (data) is most likely given the parameters, while the unconditional volatility is an empirical value. Furthermore I fit the SSM for the whole trading day and trim the first and last 15 minutes afterwards, hence the parameter estimates are with respect to the whole trading day as well. For the same reasons, the standard deviation of ϵ reported in Panel B is basically different from the volatility parameter σ_ϵ.

TABLE 3.17: **State Space Model Estimation.** The table shows summary statistics based on the output of the state space model defined by (3.11),(3.12), and (3.13). Panel A shows average parameter estimates, standard deviation, median, and inter-quartile range (IQR) for the AR-coefficient of the transitory price component and the error term volatilities. Panel B reports descriptive statistic for the Kalman smoother output, i. e., price components derived from the smoothed state variables $m_{i,t}$ and $s_{i,t}$.

Panel A: SSM Parameter Estimates	Unit	Mean	Std. Dev.	Median	IQR
AR-coefficient ϕ		0.3766	0.4142	0.4415	0.7512
Permanent innovation volatility σ_η	bps	7.3501	4.4219	6.1906	3.9199
Transitory error volatility σ_ϵ	bps	2.0290	2.9620	1.1323	2.8434
Panel B: SSM Components					
Permanent innovation ($\eta_{i,t}$)	bps	-0.0091	7.9352	0.0000	4.9073
Transitory component ($s_{i,t}$)	bps	0.0009	2.8456	0.0000	0.1996
Transitory component ratio	%	23.0402	29.3000	8.1728	39.3972
Transitory error ($\epsilon_{i,t}$)	bps	0.0002	2.3200	0.0000	0.1595
Transitory error ratio	%	19.9048	25.2823	7.6245	33.7491

Table 3.17, Panel B presents descriptive statistics for the smoothed SSM components and the ratios defined above. The SSM estimates indicate that on average the transitory innovation accounts for 23% of the total fluctuation in the model components, on average.

To relate the SSM output to the defined TA-based trading signals, I merge the SMA long and short as well as the SRL indicators with the (smoothed) SSM components. For smoothed pricing errors $s_{i,t}$ of stock i at time t I estimate a regression model containing only intercept and TA indicator variables and an extended model specification defined by

$$\begin{aligned} s_{i,t} = \alpha + \beta_1 TA1_{i,t} + \beta_2 TA2_{i,t} + \delta_1 \widetilde{VDAX}_{i,t} \mathbf{1}_{(s_{i,t}>0)} \\ + \delta_2 \widetilde{VDAX}_{i,t} \mathbf{1}_{(s_{i,t}<0)} + \delta_3 \widetilde{MCap}_{i,t} \mathbf{1}_{(s_{i,t}>0)} + \delta_4 \widetilde{MCap}_{i,t} \mathbf{1}_{(s_{i,t}<0)}, \end{aligned} \tag{3.15}$$

where $\mathbf{1}_{(\cdot)}$ is the indicator function and $\widetilde{VDAX}$ and $\widetilde{MCap}$ denote standardized *VDAX* and market capitalization. Since idiosyncratic stock volatility is typically correlated with market volatility (Guo and Savickas, 2006), we can expect that market volatility is related to the size of pricing errors given the ratio of permanent and transitory effects is unchanged. Thus, I split the effects for positive and negative values of $s_{i,t}$. As before, the models are estimated for SRL and SMA signals separately. For $PEshare_{i,t}$ and $TIshare_{i,t}$ the respective regression models include TA indicator variables, $\widetilde{VDAX}$, $\widetilde{MCap}$ and stock fixed effects. Because both ratios should not be affected by market volatility and capitalization in a non-linear way, the model includes both variables as they are. All regression models use stock-day double clustered standard errors as proposed by Thompson (2011).

I estimate the defined regression models from the SSM output and use all observations between 09:15 and 17:15. The latter should reduce the influence of extreme values at the boundaries of the time series[18].

Table 3.18 shows the regression results. Panel A reports models including SRL indicators. Models (i) and (ii) indicate that pricing errors tend to be more negative at support levels and more positive at resistance levels. This means transitory price deviations appear in direction of support levels and resistance levels, respectively. Thus, quoted prices tend to be too high (too low) at resistance (support) levels. The estimated coefficient imply (absolute) pricing errors ranging between 0.29 bps and 0.34 bps. The effect is also present after controlling for external factors. Higher market capitalization has no significant effect while the sign of both estimates suggests a negative relation to the size of pricing errors. Market volatility is associated with both large positive and negative pricing errors.

The latter is considered more detailed in models (iii)-(vi) where the ratios defined by (3.14) are taken as independent variables. Thereby I control for the case that transitory and permanent component increase proportionally. The results are very similar across the four models indicating that the proportion of pricing error in total price change is significantly larger around SRL, respectively. Depending on the model, the estimates

[18] This can arise from higher uncertainty in the trading process itself as well as from fitting the SSM model which can exhibit boundary effects.

TABLE 3.18: **Regression Model of SSM Price Components.** This table presents results from regressing price components on TA indicators. The pricing error is derived from the SSM model defined by equations (3.11), (3.12), and (3.13). Error ratio sets the absolute pricing error in relation to the sum of absolute pricing error and permanent innovation. Analogously, innovation ratio utilizes the transitory innovation instead of the pricing error. Panel A and Panel B show results from regressions employing support and resistance level indicators and moving average indicators, respectively. Models (i), (iii), and (v) include an intercept and TA indicator variables only, while models (iv) and (vi) control for market volatility (VDAX) as well as market capitalization and apply stock fixed effects. In model (ii) the VDAX and market cap effect is separated depending on the sign of the independent variable as specified in equation (3.15). All models contain standard errors double-clustered on stock and day. *, **, *** denote significance on a 10%, 5%, and 1% level, respectively. Standard errors are reported in parentheses.

Panel A:		Pricing Error		Error ratio		Innovation ratio	
Support & Resistance		(i)	(ii)	(iii)	(iv)	(v)	(vi)
Intercept		0.0007	-0.0002	22.8376***		19.7433***	
		(0.0006)	(0.0005)	(0.6467)		(0.5064)	
At support		-0.3147***	-0.3434***	4.4104***	3.3983***	3.5426***	2.7115***
		(0.0236)	(0.0227)	(0.5076)	(0.4587)	(0.4394)	(0.3828)
At resistance		0.2901***	0.3226***	4.8947***	4.0136***	3.8778***	3.1482***
		(0.0202)	(0.0208)	(0.4591)	(0.4354)	(0.4112)	(0.3730)
VDAX	$\times\mathbf{1}_{y_t>0}$		0.6173***				
			(0.0658)		0.8189***		0.7168***
	$\times\mathbf{1}_{y_t<0}$		-0.6244***		(0.3342)		(0.307)
			(0.0658)				
Market cap	$\times\mathbf{1}_{y_t>0}$		-0.0420				
			(0.0998)		-0.6511**		-0.4000
	$\times\mathbf{1}_{y_t<0}$		0.0411		(0.3842)		(0.3435)
			(0.0995)				
Fixed effects		no	no	no	yes	no	yes
Panel B: Moving Averages							
Intercept		0.0012**	0.0005	23.0551***		19.9275***	
		(0.0005)	(0.0005)	(0.6590)		(0.5177)	
SMA long		0.8931***	0.8636***	-1.4830***	-1.5624***	-2.3190***	-2.3867***
		(0.0637)	(0.0610)	(0.3181)	(0.3134)	(0.3042)	(0.3003)
SMA short		-0.9583***	-0.9308***	-1.6344***	-1.7104***	-2.4301***	-2.4936***
		(0.0801)	(0.0778)	(0.3218)	(0.3151)	(0.2974)	(0.2918)
VDAX	$\times\mathbf{1}_{y_t>0}$		0.6217***				
			(0.0682)		9.2606***		7.5421***
	$\times\mathbf{1}_{y_t<0}$		-0.6310***		(3.2736)		(2.9032)
			(0.0682)				
Market cap	$\times\mathbf{1}_{y_t>0}$		-0.0003				
			(0.0317)		-1.5640**		-1.4001**
	$\times\mathbf{1}_{y_t<0}$		-0.0025		(0.7335)		(0.6559)
			(0.0320)				
Fixed effects		no	no	no	yes	no	yes

imply an increase of 14.7% - 21.2% of the average pricing error share around support or resistance levels (15.8% - 20.1% for the transitory innovation share).

Panel B of Table 3.18 presents the estimation results for models including SMA signal indicators. Model (i) and (ii) show that pricing errors are significantly positive (negative) when an SMA long (short) signal is triggered implying that quoted prices are above efficient prices. The coefficient implies overpricing (underpricing) at SMA long (short) signals of 0.89 bps (0.95 bps) which is about 30% of the transitory component standard deviation. Thus the effect appears to be stronger as in case of SRL.

Considering the transitory component shares, the significant pricing errors do not lead to a larger proportion of the transitory price component, however. Models (iii) and (iv) indicate a decrease of 1.48% to 1.71% in the pricing error share. For the transitory innovation share a decrease of 2.3% to 2.5% is estimated. While SMA signals can be associated with the direction of the pricing error and its absolute size[19], the denomination through the permanent innovation component shows that relative values are slightly decreasing. I also estimate models for permanent price components $w_{i,t}$ (not reported) showing a positive (negative) effect for SMA long (short) signals. Price movements are generally of larger magnitude around SMA signals which is driven by both more extreme pricing errors and permanent price innovations.

Discussion of Results

In case of resistance levels where the midquote price is closely below a specific price level the pricing error tends to be more positive implying overpricing. As shown in Section 3.6.3, such levels are associated with excess limit order book volume. Overpricing implies that informed traders would sell in this situation. However, if quoted spreads are larger than the pricing error, they can realize potential profits only by placing aggressive limit orders which could account for the increased depth at the best ask. The presented evidence regarding excess depth being already visible in the LOB before the support or resistance level reaches best bid or ask contradicts this mechanism, though. On the other hand, if the depth increase means that limit order cluster at a specific level instead of being distributed over several levels, price discovery could be distorted in

[19] I also estimate models with absolute pricing errors yielding a similar result as (i) and (ii). For brevity, these results are not reported.

the sense that liquidity demand of a given size has a greater impact and prices tend to overshoot until the price level of increased supply is reached. In this scenario, we would find overpricing (underpricing) in front of resistance (support) level.

In case of SMA signals, the increased liquidity demand in the direction of the SMA signal might not be compensated immediately. If directional excess liquidity demand occurs over a long period then the price change becomes persistent. Varying signal processing times of Technical Analysis traders and the application of different trigger conditions could spread the demand for liquidity over some period of time. If the uninformed liquidity demand is (expected to be) persistent, the short-term risk for informed trader increases and could limit arbitrage trading (De Long et al., 1990b; Bloomfield et al., 2009). In this scenario, the increase in the size of transitory and permanent price components, i. e., short-term price volatility, would be due to directional noise trading that discourages informed traders (arbitrageurs) and liquidity suppliers to trade in the opposite direction. Eventually prices would revert after liquidity demand in direction of the signal vanishes.

Overall, both types of TA signals are associated with increased fluctuations in pricing errors supporting item (ii) of Hypothesis 2b. In case of SMA the increase in permanent component outweighs the transitory part which contradicts the statement on permanent price changes in this hypothesis but reveals a different view on the effect of TA-related trading. Section 3.6.6 presents further evidence on the volatility of transitory and permanent price components on a higher frequency, which confirms the results of this section.

3.6.6 Robustness Tests

Liquidity Measures

To check the robustness of results presented in the previous sections, I use two alternative approaches to test the relation between liquidity measures and TA indicator. First, models of type (3.9) for yearly subsamples assess whether effects remain stable over time. The regressions apply the same independent variables but employ standard errors double clustered by stock and day (Thompson, 2011). Additionally, I use an alternative approach to analyze liquidity measures. In a first step, I fit an auto-regressive model of the variables of interest for each stock-day. The model includes five lags and a second-order trend. The residuals of all stock-days are then pooled and regressed on the TA indicators and control variables as before. Since residuals have zero-mean across stocks and days, stock-day fixed effects are not included. The quadratic trend and the inclusion of lags incorporate an alternative intraday variation structure that replaces the minutely fixed effects of the original model. In sum, I estimate a model of type (3.9) with double clustered standard errors and a simple intercept instead of fixed effects. The main purpose of this approach is to account for potential stock- and time-varying auto-regressive characteristics in the analyzed liquidity measures.

Columns '2008' - '2013' of Table 3.19 report results for the measures turnover, quoted spread, effective spreads, Depth5 Ask, and Depth5 Bid for each year. For the sake of brevity the table solely contains the TA indicator estimates. Column 'All' shows results for the respective model of AR(5) residuals. The latter confirms the findings regarding SRL, i. e., significantly positive SRL indicator estimates for quoted and effective spreads as well as for depth on the side of the respective SRL. The year-by-year consideration shows that LOB depth on ask (bid) side at resistance (support) levels is significantly increased throughout the samples. For quoted spreads, I find no significant SRL estimates in 2008 and relatively large estimates accompanied with high standard deviation in 2009. Similar results occur for effective spreads. The generally stressed market situation during the financial crisis might be a reason for the different results for the spread measures in these years.

Panel B reports models including SMA indicators. As before, findings from the main analyses can be confirmed. Turnover surges around long and short signals in all years. The coefficients suggest that the effect on turnover is particularly strong at the beginning of the sample. Analogues assertions hold for quoted spreads while in case of effective spreads the evidence is relatively mixed throughout the years. Interestingly, the approach based on AR(5) residuals also suggests a significantly positive effect on effective spreads. I interpret this results as additional evidence against Hypothesis 1b, (iii).

TABLE 3.19: **Robustness Checks for Liquidity Measures.** The table presents robustness tests for several liquidity measures used in main analyses. Columns '2008' - '2013' report regressions of type (3.9) which employ standard errors double-clustered by stock and day. The model is estimated for each year separately. The regression specifications contain stock, day, and minute dummies. Column 'All' reports results from a two stage approach. First, an auto-regressive model including five lags and a quadratic trend is fitted for each stock-day. Then the model residuals are regressed on TA indicator variables and controls. Standard errors are double clustered by stock and day. Panel A and Panel B show results for support and resistance levels and moving average trading signals, respectively. Values for control variables are omitted. *, **, *** denote significance on a 10%, 5%, and 1% level, respectively. Standard errors are reported in parentheses.

Panel A: Support and Resistance		2008	2009	2010	2011	2012	2013	All
Turnover	At Support	-56.9826*	-9.2411*	-12.9413***	-18.7801***	-6.0181***	-6.9385***	0.2081
		(12.5708)	(6.2046)	(4.4653)	(5.1851)	(1.9602)	(2.9107)	(1.9195)
	At Resistance	-51.0872***	-10.1663***	-19.3840***	-26.7549***	-7.9246***	-5.4381***	3.0691*
		(14.3908)	(4.3608)	(5.6256)	(8.8505)	(2.0786)	(2.1081)	(2.2053)
Quoted Spread	At Support	0.1595*	0.7406*	0.1227***	0.1560***	0.1946***	0.1254***	0.0531***
		(0.1261)	(0.5169)	(0.0316)	(0.0439)	(0.0707)	(0.0286)	(0.0078)
	At Resistance	0.1225	0.3573***	0.1175***	0.1735**	0.1675***	0.1056***	0.0503***
		(0.1062)	(0.1296)	(0.0362)	(0.0896)	(0.0574)	(0.0200)	(0.0075)
Effective Spread	At Support	0.2469*	0.5912	0.0619***	0.0591**	0.0601***	0.0427***	0.0425***
		(0.1604)	(0.4631)	(0.0181)	(0.0319)	(0.0172)	(0.0183)	(0.0095)
	At Resistance	0.2817**	0.2190*	0.0578***	0.0587**	0.0663***	0.0346***	0.0360***
		(0.1335)	(0.1412)	(0.0167)	(0.0262)	(0.0203)	(0.0124)	(0.0060)
Depth5 Ask	At Support	212.2236**	6.8103	75.3086*	91.6682**	12.5037	33.1957***	-0.5390
		(104.6517)	(8.6867)	(53.4369)	(44.2051)	(11.0213)	(11.6925)	(0.5909)
	At Resistance	240.2373***	93.1328***	158.5761**	193.4304***	119.4657***	138.0345***	6.4670***
		(94.1351)	(36.1803)	(80.0895)	(62.6305)	(28.6488)	(32.7405)	(0.5888)
Depth5 Bid	At Support	354.9068**	61.6024***	130.6859**	155.1138***	72.6739***	90.2272***	5.2602***
		(175.9610)	(23.6755)	(67.9420)	(58.6421)	(12.9476)	(18.6673)	(0.6151)
	At Resistance	200.7927**	13.5104	94.2721*	111.6243***	32.2454**	51.4654***	-0.3093
		(113.7585)	(12.6604)	(61.0151)	(46.6665)	(16.6709)	(16.3957)	(0.5733)

Continued on next page

Continued from last page

Panel B: Moving Averages		2008	2009	2010	2011	2012	2013	All
Turnover	SMA long	62.3965***	24.8750***	13.2210***	12.0036**	18.1904***	15.8653**	5.8742***
		(17.2978)	(6.4682)	(5.4964)	(5.7621)	(6.8118)	(6.9554)	(1.9711)
	SMA short	67.3643***	24.5664***	18.7749***	17.6065***	23.0853***	16.1618***	5.0113***
		(17.1334)	(6.5737)	(6.7353)	(7.4462)	(6.2471)	(5.742)	(2.0543)
Quoted Spread	SMA long	0.8814***	1.0505***	0.3431***	0.3329***	0.3434*	0.1768***	0.0854***
		(0.2402)	(0.4223)	(0.0821)	(0.1009)	(0.2145)	(0.0191)	(0.0094)
	SMA short	0.9824***	1.1583***	0.3638***	0.3449***	0.4157**	0.1809***	0.1050***
		(0.2908)	(0.4559)	(0.0722)	(0.0982)	(0.2509)	(0.0263)	(0.0106)
Effective Spread	SMA long	-0.0411	0.2919**	0.1646***	0.1661***	0.0795**	0.1143***	0.0546***
		(0.1744)	(0.1765)	(0.0399)	(0.0475)	(0.0365)	(0.0161)	(0.0076)
	SMA short	0.0062	0.3480**	0.1527***	0.1803***	0.1177***	0.0921***	0.0732***
		(0.2048)	(0.1634)	(0.0329)	(0.0467)	(0.0297)	(0.0244)	(0.0080)
Depth5 Ask	SMA long	-44.9903**	3.0351	-7.1237	-14.6240**	-15.2979***	-31.6890***	4.4170***
		(20.7447)	(6.7904)	(7.6407)	(6.52)	(5.0345)	(9.3374)	(0.5360)
	SMA short	-51.4653**	-42.2893***	-44.0597***	-39.3492***	-41.9796***	-64.7970***	-7.8998***
		(27.0127)	(13.739)	(8.1225)	(9.177)	(7.8715)	(12.2583)	(0.6817)
Depth5 Bid	SMA long	-66.2827***	-34.9878***	-38.3106***	-31.9072***	-34.4710***	-54.9490***	-7.6556***
		(26.0252)	(11.0987)	(7.3471)	(7.8703)	(6.6846)	(10.4196)	(0.6391)
	SMA short	-44.0957**	7.3535*	-6.7537	-13.0962**	-12.3747***	-31.9159***	3.1128***
		(23.2831)	(4.984)	(7.1382)	(6.7383)	(4.9091)	(10.2555)	(0.4914)

Volatility of Transitory and Permanent Price Components

In Section 3.6.5, I use the SSM defined by equations (3.11), (3.12), and (3.13) to decompose minutely prices and relate the components to TA signals. Since the SSM is applied to minutely midquote prices the decomposition refers to a single point of time. This might not fully reveal effects from TA signals on prices, because trading on TA signals probably appears not instantaneously but is distributed over some period of time. Furthermore, the approach of analyzing the size of (for instance) pricing errors means considering the mean effect on the price components instead of the effect on their volatility.

To complement the above analysis, I repeat the state state procedure for midquote data with a 1-second observation frequency. The SSM definition and estimation approach remains the same. From the smoothed pricing error $s_{i,\tau}$, where τ refers to a 1-second observation, I calculate the transitory volatility

$$\sigma_{s,i,t} = \sigma(s_{i,\tau}, ..., s_{i,\tau+59}), \tag{3.16}$$

where $\tau = 60t$ and $t = 0, 1, ...,$ denotes 1-minute intervals. The permanent volatility

$$\sigma_{\eta,i,t} = \sigma(\eta_{i,\tau}, ..., \eta_{i,\tau+59}), \tag{3.17}$$

is analogously defined. From the pooled stock-minute volatilities and volatility ratios $100 * \sigma_{s,i,t} / (\sigma_{s,i,t} + \sigma_{\eta,i,t})$, I estimate regression models including SRL and SMA indicators, respectively, and a second specification adding VDAX (market volatility) and market capitalization. All models include stock-day fixed effects and double clustered standard errors.

Table 3.15 reports the results for specifications including SRL indicator variables (Panel A), and SMA long and short signals (Panel B), respectively. The increase in pricing error volatility around SRL is not significant, however the ratio of transitory volatility to total volatility shows a strong relative increase. The corresponding estimates imply a 6.11% (6.4%) increase at support (resistance) levels which appears to be substantial compared to typical levels[20]. Obviously, this is caused by the reduction in permanent volatility. For SMA signals the transitory and permanent volatility derived from the

[20]The mean volatility ratio equals 10.65%, standard deviation 23.45%

SSM increases significantly. The effect is more dominant for permanent volatility as the decreasing share (about 4%) of transitory volatility indicates.

Overall, the SSM applied to 1-second midquote data confirms the results presented in Section 3.6.5. The volatility of the transitory component around SRL provides a new perspective. It seems that the (absolute) higher pricing errors estimated on a 1-minute frequency do not vary excessively when considered on a higher frequency. Since the respective SRL indicator variable is determined with respect to a specific 1-minute quote observation, the effect could be just a single jump which does not translate into excessive further variation. Furthermore, the actual SRL level is probably not at the best bid or ask during some 1-minute period over which the transitory volatility is calculated. I also test an alternative range over which standard deviations $\sigma_{s,i,t}$ and $\sigma_{w,i,t}$ are determined. In this case, the 1-minute intervals from which standard deviations of the SSM components are calculated begin between two full minutes. The estimation results are qualitatively equal, so I omit to report the tables.

3.6.7 Conclusion

I demonstrate that two popular Technical Analysis techniques are related to significant variations in market quality measures. In 1-minute intervals with an active SRL limit order supply increases significantly and quoted as well as effective spreads are higher. In case of SMA signals, turnover and quoted spreads rise significantly. Although coefficient estimates of effective spreads are not significantly higher, I find no evidence that trading on TA signals leads to lower implicit trading costs due to potentially reduced adverse selection risk for liquidity suppliers. The analysis of realized spreads suggests that subsequent to TA signals prices tend to evolve unfavorably for Technical Analysis traders implying that trading on TA signals is not beneficial from a short-run perspective. In sum, the empirical evidence confirms part (i) and (ii) of Hypothesis 2a whereas part (iii) is rejected. In this regard, the results for Xetra contradict findings from other studies.

The analysis of SSM price components shows that Technical Analysis trading signals are related to differences in permanent and transitory price components (Hypothesis 2c). Pricing errors tend to be larger in the direction of an active support or resistance level, i. e., pricing errors are significantly positive at resistance levels and negative at

TABLE 3.20: **Regression Model of SSM Price Component Volatility.** This table presents estimation results from regressing SSM price component volatilities on TA indicators. The independent variables permanent and transitory volatility defined in (3.16) and (3.17) denote the 1-minute standard deviation of the respective price components of SSM (3.11), (3.12), and (3.13) applied to 1-second midquote prices. Vola ratio is defined as transitory volatility divided by the sum of permanent and transitory volatility. Panel A and Panel B show results for SRL and MA indicators, respectively. Models (i), (iii), and (v) contain TA indicator variables and stock-day fixed effects only, while models (iv) and (vi) additionally control for market volatility (VDAX) and market capitalization (calculated as average of the previous day). All models contain standard errors double-clustered on stock and day. *, **, *** denote significance on a 10%, 5%, and 1% level, respectively. Standard errors of the coefficient estimates are reported in parentheses.

Panel A:	Transitory Vola		Permanent Vola		Vola Ratio	
Support & Resistance	(i)	(ii)	(iii)	(iv)	(v)	(vi)
At Support	0.0090	0.0088	-0.0722***	-0.0753***	6.1107***	6.0993***
	(0.0055)	(0.0055)	(0.0073)	(0.0072)	(1.3232)	(1.3247)
At Resistance	0.0056	0.0057	-0.0868***	-0.0833***	6.4049***	6.3664***
	(0.0038)	(0.0038)	(0.0084)	(0.0082)	(1.1967)	(1.1978)
VDAX		0.0020***		0.0524		-0.3086***
		(0.0005)		(0.0031		(0.0343
Market cap		0.0000		-0.0002***		-0.0147*
		(0.0001)		(0.0002)		(0.0075)
Panel B: Moving Averages						
SMA long	0.0151***	0.0151***	0.2627***	0.2630***	-3.8650***	-3.8692***
	(0.0044)	(0.0044)	(0.0153)	(0.0153)	(0.4299)	(0.4303)
SMA short	0.0168***	0.0167***	0.2939***	0.2926***	-3.9555***	-3.9490***
	(0.0046)	(0.0046)	(0.0158)	(0.0158)	(0.4377)	(0.4373)
VDAX		0.0020***		0.0525***		-0.3178***
		(0.0005)		(0.0031		(0.0356
Market cap		0.0000		-0.0001		-0.0151*
		(0.0001)		(0.0002)		(0.0076)

support levels. For SMA signals I find overpricing after a long signal and underpricing at short signals, i. e., pricing errors are in line with the recommended trade direction. However, permanent price changes rise disproportionately compared to pricing errors implying that price moves are relatively persistent after SMA signals. The latter is an indication for persistent liquidity demand in direction of the signal which might be an explanation for rising or unchanged spreads around signals. Despite the higher probability to trade against uninformed Technical Analysis traders, liquidity suppliers would be faced with noise traders herding on one side of the market, making liquidity provision or arbitrage trading less attractive.

Assuming that the TA signals contain no fundamental information about some stock and are not systemically related to external idiosyncratic information events, my results show that price discovery is influenced by TA signals. Thus, investment heuristics as a form of behaviorally motivated trading seem to be able to influence the microstructure of stock trading in the short run. Naturally, the shown effects only explain a small portion of variation in the analyzed variables. First, signals do appear quite rarely and might be perceived differently by different traders. Second, only some fraction of market participants actually use such strategies. Yet the impact of TA signals can be observed which highlights the relevance of such believes for stock markets.

Since I have no information on the identities or even the intentions behind each trade, the study is limited by the assumption that the considered TA signals are actually traded by a relevant number of market participants who thereby cause the shown effects. If this assumption does not hold, TA signals are nevertheless able to detect variations in liquidity and price discovery. On the other hand, the analysis of fully transparent order flows from traders using Technical Analysis or other trading heuristics could reveal further insights on the impact of trading heuristics in financial markets. In particular, a specific analysis of the question of how long-lasting price deviations of such order flows are and how they reverse, if at all. In this regard, the presented empirical evidence provides an indication of the ongoing competition between Technical Analysis noise traders and other market participants.

3.7 Summary

Technical Analysis (still) is a relevant factor for securities trading. In this chapter, I empirically show that signals from popular Technical Analysis trading strategies are related to both retail investor trading in speculative structured products as well as stock trading on Xetra.

In the case of speculative structured products traded at Stuttgart Stock Exchange, I find a 35% increase in trading activity on days of chart pattern trading signals and an 11% increase for moving average signals. Furthermore, I identify trading characteristics of round-trip trades. First, raw returns of TA-related trades are significantly higher while leverage levels at purchase are lower and the holding duration tends to be shorter. Second, the shape of the realized return distribution is significantly less left-skewed (more right-skewed). In this regard, retail investors using Technical Analysis methods might be less prone to the disposition effect due to the system-based trading approach. If we assume that a fundamental motivation of retail investors who trade speculative products is gambling and entertainment as existing literature suggests, then TA-related trades tend to reach this goal more effectively.

To analyze the immediate impact of Technical Analysis trading signals on the German stock market, I extend existing methodologies in order to account for characteristics of intraday price observations. Analyzing a 6-year sample of DAX30 stocks traded on Xetra, I find excess liquidity demand around moving average signals and high limit order supply on support and resistance levels. Depending on the type of signal, spreads increase or remain unaffected which contradicts the mitigating effect of uninformed TA-based trading on adverse selection risks. While global measures of price efficiency change little on signal days, the analysis of transitory and permanent price components demonstrates increasing pricing errors (noise) around signals. However, around moving average signals permanent price changes tend to increase of a larger magnitude. This suggests that liquidity demand in direction of the signal leads to relatively long-lasting price deviations which might be an explanation for the shown surge in spread measures.

Chapter 4

Round Number Effects

4.1 Introduction

In an idealized market the fair value of an asset at a fixed point in time is a unique and precise number. In this idealized scenario, we would expect this value to assume any number. However, this number – and thus the value of the asset – depends on the market design and trading mechanism in several ways. In stock markets, and in other markets alike, the value depends on the supply and the demand in the traded asset. Limit order book markets bring together the supply and demand side. Market participants place limit orders to make an offer to trade a quantity up to a designated limit price. If the order cannot be matched with existing orders in the orderbook, the trader is considered as a liquidity supplier who offers other market participants an opportunity to trade. Liquidity demander may accept the offer by submitting a market (marketable) order. This mechanism reveals the current price of the traded asset. As a result, asset prices are affected by human perception of the prices offered by liquidity suppliers and by the usage of numbers when offering liquidity, i. e., when the investors specifies the the limit price of the limit order she wants to submit.

In practice, aspects of market design influence the possible numbers values can assume. Exchange operators of limit order book markets specify a set of permitted price values which is typically defined by the minimum price increment, that is, the so-called tick-size. Furthermore, the stock company itself influences the typical price range of their stock by specifying the number of shares into which the equity of the company is divided. Stock splits (and reverse splits) are often used to have a share price in some convenient price (number) range, e. g., between EUR 10 and EUR 100.

While the price that is realized as a result of the price determination function of financial markets could basically be any number, the human perception and usage of numbers is biased in various ways. Rosch (1975) finds that experiment participants use multiples of ten as cognitive reference points. The frequently occurring pricing of consumer goods exactly below integers has been studied extensively in the marketing literature, see Thomas and Morwitz (2005) and citations therein. Brenner and Brenner (1982) put forward that humans give greater significance on the first digits of a number which is commonly exploited by vendors. clustering, buy-sell imbalances, or other number effects.

In the context of financial markets, Harris (1991) points out the need of traders to simplify their negotiations and, thus, they concentrate on a smaller set of prices. Mitchell (2001) states that using round numbers is more convenient and simplifies calculations and memory. I refer to the latter paper for a detailed discussion of psychological effects regarding number preferences and the human usage of numbers.

A typical characteristic of limit order markets is clustering of limit orders and transaction prices around certain price levels. Price clustering in financial markets has been studied over many decades. For instance, Osborne (1962) and Niederhoffer (1965) obverse that trade prices are more often round numbers than one would expect. Other empirical studies have investigated the occurrence of price clustering in different markets, assets, and countries. In general, there are several forms of biases and anomalies related to numbers, e. g., price clustering, buy-sell imbalances, and threshold effects. Throughout the text, I use the term round number effects denote any form of market or price anomaly related to numbers.

Hasbrouck (1999) introduces a structural model of bid and ask dynamics. The model accounts for price discreteness and clustering by adding a rounding mechanism which rounds to the minimum tick size or to multiples of five. However the model does not allow for buy-sell probabilities that depend on the roundness of bid and ask prices. Bhattacharya, Holden, and Jacobsen (2012) – henceforth referred to as BHJ – extend the analysis of all transaction prices by differentiating between buy and sell orders of liquidity demanders which allows to calculate buy-sell imbalances with respect to transaction prices. BHJ study buy-sell imbalances in 100 stocks traded on the NYSE during the time period from 2001 to 2006. They find that investors have a preferred hierarchy of roundness which is whole dollars, half-dollars, quarter, dimes, and nickels which is inferred from the increased number of buys (sells) below (above) these thresholds. Further, they test three different explanations for the occurrence of buy-sell imbalances, namely undercutting, left-digit effects, and threshold trigger effects. They find evidence for all three effects, but undercutting appears to be the most dominant while the others are relatively weak. In their conclusion, BHJ highlight the question whether round number effects can be found in other markets and other countries.

On the other hand, the electronic evolution of financial market and the huge success of trading algorithms could challenge whether the scenario by BHJ, i. e., value traders, who are influenced by their perception of round numbers and, thus, alter their buying and selling behavior, still holds. This motivates the main research question for this chapter.

Research Question 3. *How do round number effects influence trading on the German stock market?*

To answer this question, I consider five years of high-frequency data from Xetra and find strong evidence that round number effects are also present in Germany. My overall results for DAX30 stocks traded on Xetra show about 21% more buys below an integer price level and 17% more sells above an integer price level, for example. This holds true for other round number thresholds like 50, 20, and 10 cent with decreasing imbalance values. However, investors in German markets have different cognitive reference points than Americans, which seems to be related to characteristics of the local currency. German investors do not focus on prices which are uneven multiples of a quarter. Instead multiples of 20 seem to be (more) preferred. Overall, the order of preference fits with the available Euro coins in an analogues manner to the NYSE and the US Dollar coins.

Furthermore, trends and determinants of round number effects are identified such as a decreasing effect strength over time, a positive relation to market capitalization, and the role of tick size rules. The analysis of retail investor trading at Stuttgart

Stock Exchange reveals that the magnitude of human round number biases is larger and remains stable over time. The main reason for number biases in trades of retail investors seems to be the usage limit order prices.

The research presented in this chapter provides empirical evidence on the existence and the characteristics of round number effects in the German stock market and thereby complements existing literature on round number effects in financial markets. By identifying trends and determinants of round number effects, I contribute to the deeper understanding of this anomaly. Furthermore, the analysis of retail investor trading data allows for new insights regarding the mechanism in which (human) number biases convey to trading and asset prices.

The remainder of this chapter is structured as follows. The following section outlines the research approach and discusses related literature. The sample selection used to conduct the empirical analyses is described in Section 4.3. Section 4.4 analyzes buy-sell imbalances on Xetra using two methodologies. Section 4.5 assesses potential determinants of round number effects. A specific study of retail investor trades at Stuttgart Stock Exchange is performed in Section 4.6. Eventually, Section 4.7 concludes.

4.2 Research Questions

Limit order clustering has been studied in many studies over several decades and is considered as a basic characteristic of limit order book markets. I refer to the literature overviews by Aitken et al. (1996), p.299-303, and Bhattacharya et al. (2012), p.415-416, for an extensive discussion of existing empirical literature. BHJ consider the relation of round number effects to the buying and selling propensity. They classify three round number effects. First, the left-digit effect, which states that a change of the left-most digit is perceived as a larger or more important price change than a price change of the same size but without a change in the left-most digit. Second, the threshold trigger effect accounts for the preference of investors to act when round numbers occur, for example placing a market order or using stop-loss orders with a round stop-price. Third, the so-called (cluster) undercutting effect denotes the behavior of market participants to increase the execution probability of their limit order by entering a limit price which is one tick better than the current best bid or ask. If limit orders are clustered at some level of the orderbook, then undercutting these clusters would be even more attractive to increase the execution probability. Logically, cluster undercutting should occur more often when there is more orderbook depth which reduces the chance that a quoted price level gets breached.

To structure the research agenda within this chapter, the overarching Research Question 3 is divided into three parts. The first part assesses whether the results of BHJ apply to the German market and which of the three above mentioned effects drive buy-sell imbalances around round numbers.

Research Question 3a. *How is the propensity of buying and selling related to the roundness of trade prices?*

Besides the general existence of buy-sell imbalances, the question arises how the effects are related to other factors such as tick size and market capitalization.

Research Question 3b. *What are the determinants of round number effects?*

In the course of this question, I also consider potential time trends of this anomaly. Given the different time periods analyzed in the paper of BHJ and this thesis, potential changes in the general market environment must be considered. First of all, the technological enhancements of the market infrastructure as well as of information processing system have led to an increase in speed and liquidity in all major markets e. g., (e. g., Hendershott and Riordan, 2013; Riordan and Storkenmaier, 2012). Algorithmic trading is responsible for a great share of the overall turnover on Xetra. Since round number effects like price clustering and buy-sell imbalances are anomalies resulting from cognitive biases of humans, an alteration in these effects seems probable within a market environment that is becoming more computer-driven.

Currently, in many important stock markets algorithmic traders account for the majority of turnover in blue chip stocks. For trading in DAX30 stocks on Xetra during January 2008, the shares of algorithmic traders in marketable and non-marketable transaction volume are 52% and 50%, respectively, as reported by Hendershott and Riordan (2013). Given the assumption that algorithms are not biased by certain numbers, round number effects should decrease when there is more algorithmic trading. Second, the argument by Harris (1991) of simplified negotiation and easier calculation of round numbers should weaken in a fully electronic market. Thus, I hypothesize that round number effects on Xetra decrease over the observation period. At the same time I do not expect human (retail) investors to get rid of their number biases since psychological shortcomings, as those reported by Rosch (1975) for example, usually are not just recognized and simply diminish afterwards.

To study round number biases of human investors, data from Stuttgart Stock Exchange where algorithmic trading is not permitted provides a promising basis. The analysis of retail investor orders and trades could allow to infer insights regarding the origin of round number effects in limit order book markets which is addressed by the following research question.

Research Question 3c. *How are round number effects related to stock trading of retail investors at Stuttgart Stock Exchange and are there differences compared to Xetra?*

In relation to this question, Kuo et al. (2015) finds that retail (individual) investors submit limit orders with round limit prices more often than institutional investors. As a consequence, I hypothesize that buy-sell imbalances should be larger at Stuttgart Stock Exchange. Due to the market structure of stock trading at Stuttgart Stock Exchange, which basically detaches market and limit orders by employing market makers, it is possible to analyze both order types independently. In particular, the undercutting should play no role for market orders while left-digit and threshold trigger effect could be more important in this case. On the other hand, the specification of the limit order price constitutes a direct interaction with the market involving the usage of numbers.

4.3 Sample Selection and Descriptive Statistics

For the empirical analyses three samples of the data sets introduced in Section 2.2 are used. To clarify the presence of round number effects in the German stock market, the 30 DAX and 50 MDAX constituents based on the index compositions on December 31, 2012 are considered. At the beginning of 2010, Deutsche Börse introduced a new tick size rule on Xetra, which is valid for the remaining observation period. Before 2010 the tick size was EUR 0.01 for all stocks. Afterwards, tick size steps have been EUR 0.001

for stocks traded below EUR 10, EUR 0.005 for stock prices between EUR 10 and EUR 50, EUR 0.01 for stock prices EUR 50 and EUR 100, and EUR 0.05 for stock prices above EUR 100. Therefore, trades above EUR 100 are disregarded. Possible implications of different tick sizes are discussed within Section 4.5. Trades below EUR 2 are dismissed because the realized price range during a year is too narrow to deduce implications regarding the cent amount of trade prices. In other words, for stocks having low prices, it is not adequate to assume equally distributed cent amounts of trade prices during a period of one year. A minimum price of EUR 5 is also tested, which does not affect the results in any form. The final data sets contain 146,856,827 trades in DAX30 stocks and 51,252,513 trades in MDAX50 stocks.

All buys and sells are classified by the cent amount of the trade price. Due to the new tick size rule introduced by the Deutsche Börse, which allows a minimum price change of EUR 0.001 for stocks traded below EUR 10, there are 1000 possible cent amounts. To maintain comparability with BHJ and to have enough observations in each group, I use 100 groups, i. e., zero to 99, and classify the non-integer trade prices as follows. Groups which are multiples of five, i. e., $N = \{0, 5, 10, ..., 95\}$, only contain trades having the exact cent amounts since these 'round' trade prices are of main interest. $N + 1$ ($N - 1$) contains all cent amounts up to one cent larger (smaller) than N. Note that one cent smaller than 0 cent means 99 cent and vice versa. The groups $N + 2$ and $N + 3$ include all cent amounts in the intervals $(N + 1, N + 2.5]$ and $(N + 2.5, N + 4)$, respectively. This classifications avoids asymmetric biases in groups below and above round numbers compared to simple rounding to the next integer.

To analyze round number effects for transactions in which retail investors are involved, I use the orderflow data from the Stuttgart Stock Exchange. The data ranges from 04/01/2009 to 12/31/2013 and contains order submissions and executions in DAX stocks. To study round number effects, I apply the same methodology as introduced above to the data from Stuttgart Stock Exchange.

Table 4.1 provides descriptive statistics for each data set and each year of the sample period. The increasing average trade price in DAX and MDAX stocks might have an impact on the results since round number effects are expected to be larger when prices are high. Section 4.5 discusses possible implications in detail. The overall turnover and the number of transactions are much smaller at Stuttgart Stock Exchange which is a

TABLE 4.1: **Descriptive Statistics.** This table describes the data samples used within the chapter. Panel A and B show Times & Sales data of DAX30 and MDAX50 stocks traded on Xetra range from 2009/01/01 to 2013/12/31. Panel C describes trade data for DAX30 stocks traded on Stuttgart Stock Exchange ranging from 2009/04/01 to 2013/12/31. All spread measures are trade-based averages and reported as equal-weighted half-spreads. Units are given in brackets.

Panel A: DAX30 on Xetra	Overall	2009	2010	2011	2012	2013
Number of Trades [mio]	175.22	32.75	34.85	44.95	34.31	28.36
Total turnover [bnEUR]	3,635.70	705.50	808.96	857.25	667.16	596.83
Average Trade Price [EUR]	43.72	37.51	43.73	43.96	46.17	47.50
Average Trade Size [EUR]	20,749	21,543	23,212	19,070	19,447	21,041
Average eff. Spread [bps]	27.41	35.48	26.03	30.23	22.28	21.53
Average spread costs per trade [EUR]	12.31	16.85	13.28	11.14	9.96	10.58
Panel B: MDAX50 on Xetra						
Number of Trades [mio]	63.61	9.53	11.03	16.37	14.32	12.36
Total turnover [bnEUR]	510.55	90.02	108.50	126.79	95.41	89.84
Average Trade Price [EUR]	36.53	30.98	37.03	37.09	36.51	39.62
Average Trade Size [EUR]	8,026	9,443	9,841	7,744	6,661	7,267
Average eff. Spread [bps]	58.66	81.17	56.02	64.48	49.03	47.08
Average spread costs per trade [EUR]	6.55	9.86	7.41	6.22	4.78	5.74
Panel C: DAX30 on Stuttgart Stock Exchange						
Number of Trades [mio]	1.62	0.2581	0.2834	0.4090	0.3204	0.3491
Total turnover [bn EUR]	21.31	3.1341	3.4966	4.9618	4.3518	5.3655
Average Trade Price [EUR]	42.51	32.33	40.60	41.94	42.68	52.08
Average Trade Size [EUR]	13,155	12,143	12,339	12,133	13,585	15,368

limitation of the data set. Average trade size of retail investors is typically smaller, but the average share price is very close to Xetra.

4.4 Buy-Sell Imbalances of Liquidity Demanders

To study the general presence of round number effects in the German market, I use the approaches applied by BHJ for the NYSE. First, the 'unconditional analysis' considers buy-sell imbalances on a firm-year basis grouped by the cent amount of trade prices. Then the 'conditional analysis' examines all trades conditioned on the past development of quotes and transaction prices to explain the origin of buy-sell imbalances around

round numbers.

4.4.1 Unconditional Buy-Sell Imbalances

For each firm contained in the DAX and MDAX, respectively, and each year, I calculate three imbalance measures from a liquidity demander perspective. The measures are based on the number of orders, the number of traded shares, and trade turnover, i. e.,

$$\text{OrderImba}(c) = \log\left(\frac{\#\text{buys}(c)}{\#\text{sells}(c)}\right), \tag{4.1}$$

$$\text{ShareImba}(c) = \log\left(\frac{\#\text{shares bought}(c)}{\#\text{shares sold}(c)}\right), \tag{4.2}$$

$$\text{TurnoverImba}(c) = \log\left(\frac{\text{turnover buys}(c)}{\text{turnover sells}(c)}\right), \tag{4.3}$$

where $c \in \{0, 1, ...99\}$ denotes the cent classification groups defined in Section 4.3. This results in 100 imbalances for each stock and year. If a stock has less than 52 (liquidity demanding) buys or sells in the above defined price range during a year, the particular observation is dropped out. Thereby large imbalances due to only few observed trades in a particular group are avoided. This might occur when stocks were only traded for a short period within the specified price range during a year. Taking logarithms of the buy-sell imbalance ratios ensures a symmetric relation of buys to sells around zero.

Each measure controls for different aspects that could affect the validity of results drawn from a single measure. More precisely, the imbalance based on the number of orders might be affected by traders splitting large orders into smaller pieces, which is not the case for volume and turnover imbalances. On the other hand, volume could be influenced by the price level of a stock, which plays no role for turnover imbalances. The latter however could put too much weight on large trades and therefore does not represent the majority of market participants.

Figure 4.1 shows the mean of buy-sell order imbalances based on all DAX firms and years for each cent amount group. If there is no preference on specific price points such as integer prices, one would expect more or less the same ratio for all cent values. Obviously Figure 4.1 shows a clear pattern which is confirmed by both other measures depicted in Figure 4.2. Turnover imbalance and shares traded imbalance tend to be

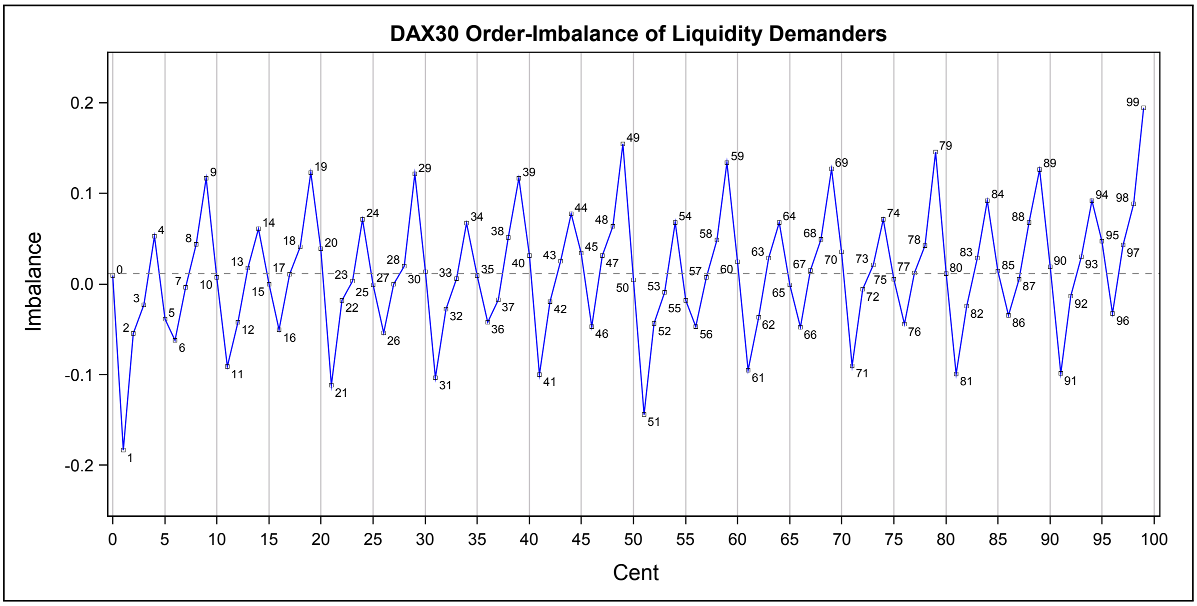

FIGURE 4.1: **DAX30 Buy-sell Order-Imbalance of Liquidity Demanding Orders on Xetra.** Average buy-sell order imbalance of DAX30 stocks from 2009 to 2013. The dashed line represents the overall buy-sell imbalance of 0.0153.

noisier since these ratios inherit much larger variance than the trade direction indicators which can only take the values 1 or -1. All imbalances show that buys greatly outnumber sells below round numbers whereas sells outnumber buys above round numbers. The differences in imbalances are of (economically) significant size. For example, if we compare the order imbalances around integers, there are about 21.41 percent more buys than sells for prices within the 99 cent group and 16.75 percent more sells than buys for 1 cent prices. Note that the imbalances do not state how many trades occur for a given cent amount. Actually there are much more trades exactly on round numbers than above or below, but in this case buys and sells are equally balanced and imbalances are near zero.

Considering Figures 4.1 & 4.2, the preferred order of roundness is integers, half-euros, ten-cent, and five-cent, which is deduced from the deviation from the particular mean. This is different to the NYSE results of BHJ where the order of roundness is found to be integers, half-dollars, quarters, dimes, and nickels. To manifest this difference in a statistical model, I run three regression models following BHJ's Table 1 who use the

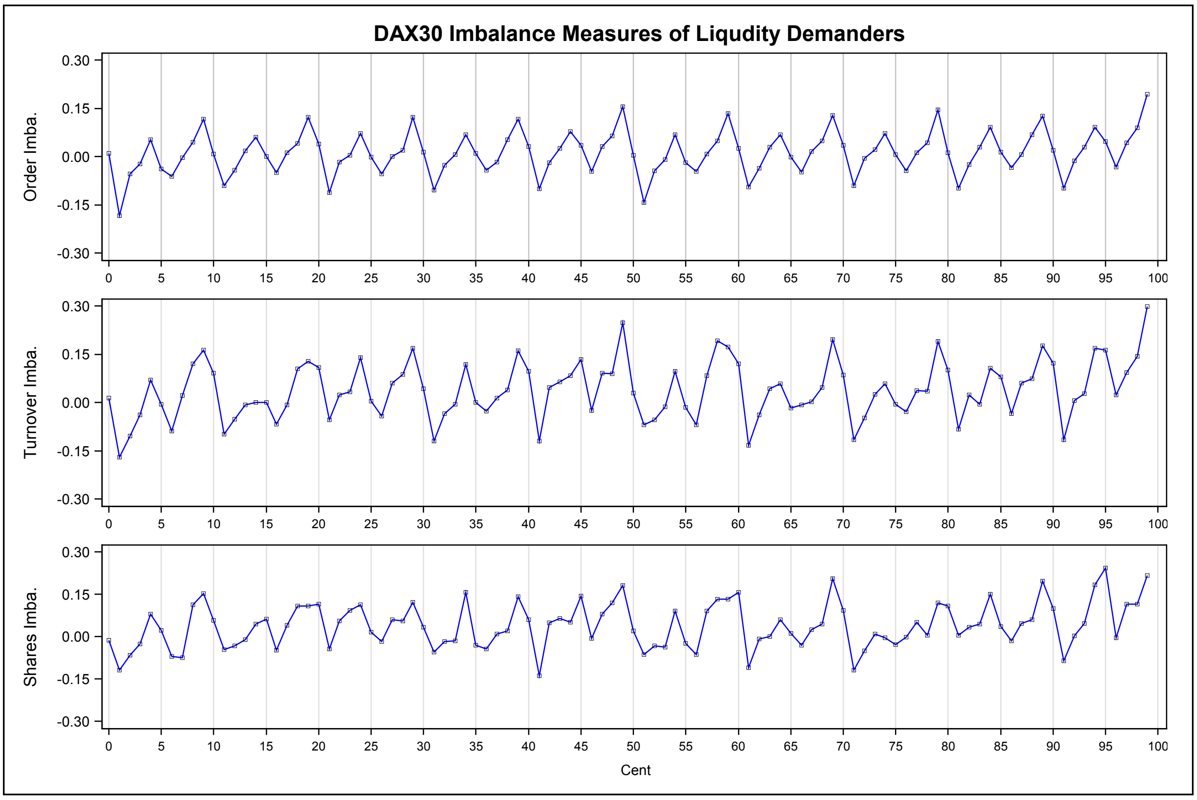

FIGURE 4.2: **DAX30 Imbalance Measures of Liquidity Demanding Orders on Xetra.** Average buy-sell imbalance measures of liquidity demanders of DAX30 stocks from 2009 to 2013. The shown measures are based on trade direction, turnover, and traded shares (from top to bottom).

regression equation

$$Imbalance = \alpha + \sum_{i=1}^{10} \beta_i * centdummy_i \, . \tag{4.4}$$

where the ten dummy variables $centdummy_i$ indicate cent amounts above and below round numbers, e. g., the below 20 cent dummy variable represents the 19, 39, 59, and 79 cent groups, and so on. Table 4.2 shows the results of regressions having dummies for below and above integers, half-Euro, 'quarter', 10 cent, and 5 cent, analogously to BHJ. For NYSE stocks they find that the absolute coefficients of these dummies are monotonically decreasing and thereby determine the order of roundness. Obviously, the order is not correct for the German market. The coefficient estimate of above (below) quarters in Table 4.2 is of the same size as the above (below) 5-cent estimate and significantly smaller (larger) than the 10-cent estimate. Wald tests and Likelihood-ratio tests are used to determine the statistical significance of the difference between two regression parameters.

The missing quarter effect in the German market could be a consequence of the fact that no 25 cent Euro coin exists, which causes German market participants to focus less on this reference point than Americans do. Additionally, the prior currency Deutsche Mark[1] did not contain quarters. German exchanges historically never relied on eight or sixteenth tick size regimes with quarters as even multiples of the minimum tick.

TABLE 4.2: **Buy-sell Ratios Regressed on Cent Dummies**. The buy-sell imbalances of liquidity demanders stock are regressed on dummies for cent amount groups (see column 1). The general regression equation is $Imba = \alpha + \sum \beta_i * centdummy_i$, $i = 1, 2, ..., 10$. Estimated coefficient standard deviations are reported in parentheses. *,**, and *** denote significance on the 5%, 1%, and 0.1% level. The sample contains DAX30 stocks traded on Xetra from January 2009 to December 2013.

	Imbalance		
	Buy/Sell Orders	Buy/Sell Turnover	Shares Bought/Sold
Intercept	0.0115***	0.0344***	0.0332***
	(0.0010)	(0.0031)	(0.0031)
Below Integers (.99)	0.2003***	0.2868***	0.2846***
	(0.0150)	(0.0274)	(0.0272)
Above Integers (.01)	-0.2059***	-0.2747***	-0.2745***
	(0.0150)	(0.0279)	(0.0278)
Below Half-Euro (.49)	0.1559***	0.2011***	0.2031***
	(0.0125)	(0.0244)	(0.0241)
Above Half-Euro (.51)	-0.1667***	-0.1674***	-0.1612***
	(0.0128)	(0.0273)	(0.0277)
Below Quarters (.24, .74)	0.0627***	0.0508**	0.0501**
	(0.0059)	(0.0175)	(0.0176)
Above Quarters (.26, .76)	-0.0649***	-0.0720***	-0.0733***
	(0.0057)	(0.0163)	(0.0162)
Below 10-Cents	0.1192***	0.1301***	0.1307***
(.09,.19,.29,.39,.59,.69,.79,.89)	(0.0031)	(0.0091)	(0.0091)
Above 10-Cents	-0.1127***	-0.1408***	-0.1402***
(.11,.21,.31,.41,.61,.71,.81,.91)	(0.0031)	(0.01)	(0.0099)
Below 5-Cents	0.0606***	0.0584***	0.0592***
(.04,.14,.34,.44,.54,.64,.85,.94)	(0.0026)	(0.009)	(0.0089)
Above 5-Cents	-0.0580***	-0.0806***	-0.0788***
(.06,.16,.36,.46,.56,.66,.86,.96)	(0.0025)	(0.0093)	(0.0092)

[1] Deutsche Mark was replaced by the Euro in 2002. Pfennig denoted the cent coins of Deutsche Mark. There were one, five, ten, and fifty Pfennig coins.

Rearranging the dummy variables to represent the existing Euro cent coins, i. e., dummies for above and below integer, half-euros, 20 cent, 10 cent, and 5 cent, shows that the order of roundness is indeed in accordance with the Euro cent coins. Consistently, the absolute value of the regression coefficients shown in Table 4.3 are monotonically decreasing. The difference between 10-cent and 20-cent coefficients is of the correct sign, although it is not statistically significant. A possible explanation might be the general importance of multiples of ten in the perception and use of numbers (cf. Rosch, 1975).

TABLE 4.3: **Buy-sell Ratios Regressed on Alternative Cent Dummies**. The buy-sell imbalances of liquidity demanders stock are regressed on dummies for cent amount groups (see column 1) which are defined according to the available Euro coins. The general regression equation is $Imba = \alpha + \sum \beta_i * centdummy_i$, $i = 1, 2, ..., 10$. Standard errors of the coefficient estimates are reported in parentheses. *,**, and *** denote significance on the 5%, 1%, and 0.1% level. The sample contains DAX30 stocks traded on Xetra from January 2009 to December 2013.

	Imbalance		
	Buy/Sell Orders	Buy/Sell Turnover	Shares Bought/Sold
Intercept	0.01148***	0.03442***	0.03324***
	(0.001)	(0.0031)	(0.0031)
Below Integers (.99)	0.20027***	0.28677***	0.28462***
	(0.015)	(0.0274)	(0.0272)
Above Integers (.01)	-0.20593***	-0.27467***	-0.27454***
	(0.015)	(0.0279)	(0.0278)
Below Half-Euro (.49)	0.15587***	0.20113***	0.20306***
	(0.0125)	(0.0244)	(0.0241)
Above Half-Euro (.51)	-0.16668***	-0.16738***	-0.16116***
	(0.0128)	(0.0273)	(0.0277)
Below 20-cents (.19, .39, .59, .79)	0.12343***	0.13541***	0.13684***
	(0.0045)	(0.0129)	(0.013)
Above 20-cents (.21, .41, .61, .81)	-0.11553***	-0.14453***	-0.14426***
	(0.0044)	(0.0142)	(0.0141)
Below 10-cents (.09, .29, .69, .89)	0.11494***	0.12471***	0.12447***
	(0.0039)	(0.0121)	(0.012)
Above 10-cents (.11, .31, .71, .91)	-0.10992***	-0.13707***	-0.13617***
	(0.0043)	(0.0134)	(0.0133)
Below 5-cents(.04, .14, .24, .34, .44, .54, .64, .74, .85, .94)	0.06101***	0.05685***	0.05741***
	(0.0024)	(0.0082)	(0.0081)
Above 5-cents(.06, .16, .26, .36, .46, .56, .66, .76, .86, .96)	-0.05934***	-0.07889***	-0.07769***
	(0.0024)	(0.0083)	(0.0082)

Extending the BHJ specification, I estimate models with both sets of cent dummies and further control variables (e. g., average spread measures) as well as stock and day fixed effects. The cent dummy coefficient estimates and standard deviations are virtually unchanged. Thus, the corresponding tables are omitted.

Summarizing on Research Question 3a, the relation between cent endings of trade prices and buying and selling intensity of liquidity demanders exists in the German market but has different characteristics. In both the U.S. and the German stock market the order of magnitude of buy-sell imbalances is in accordance to the coins of the local currency, which means that round number effects are influenced by local characteristics of market participants. The fact that market participants are familiar with their currency seems to have a direct impact on their trading behavior, i. e., they use these often perceived values as cognitive reference points.

4.4.2 Conditional Buy-Sell Imbalances

In order to determine whether unconditional round number effects are due to cluster undercutting, left-digit, or threshold trigger effects, the analysis of trade price clustering is performed conditional on the price path of bid and ask quotes. Therefore, I apply the methodology of BHJ to trades in DAX30 stocks.

All trades in the sample are classified into the following groups. 'Ask falls below integer' denotes all trades after the ask price drops from $[.0, .10]$ to below the integer until the ask leaves $[.90, .99]$. The corresponding benchmark group 'ask falls below 5-cent' contains all trades after the ask falls from $[N, N + .10]$ below N until it leaves $[N - .10, N]$, where $N \in \{.15, .25, .35, .45, .55, .65, .75, .85\}$. Omitting .05 and .95 ensures that the groups remain disjoint. Both threshold trigger and left-digit effect predict excess buying for the 'ask falls below integer' group.

'Ask falls to integer' corresponds to all trades after the ask falls from $[.01, .10]$ exactly to the integer, i. e., $[.00]$, until the ask leaves the integer price and equivalently 'ask falls to 5-cent'. Here, only the threshold trigger effect causes positive buy-sell imbalances since the left-digit of the ask price does not change. 'Ask rises while staying below integer' means all trades after the ask rises from $[.80, .89]$ to $[.90, .99]$ until the ask leaves the latter interval. The corresponding 5-cent group 'ask rises while staying below 5-cent' aggregates all trades after the ask soars from $[M-.20, M-.11]$ to $[M-.10, M-.01]$, where $M \in \{.25, .35, .45, .55, .65, .75\}$, until the ask leaves $[M-.10, M-.01]$. Again, the thresholds for M are chosen to ensure disjoint integer and 5-cent groups.

BHJ use the latter groups as a way to control for the meaningfulness of the other two groups. Moreover, this group could represent the situation when traders start to sell below resistance levels, i. e., price barriers which they believe will not be penetrated. Note that this kind of situation does not fit within BHJ's framework of value investors using market orders according to their valuation of a stock which only predicts positive (negative) imbalances when prices fall (rise). I avoid this scenario since value traders who submit market orders seem to be neither the only nor the main cause for the observed phenomenon. BHJ as well as this study conclude that round number effects are primarily driven by traders submitting limit orders and maybe other traders reacting to the fact that existing orders in the limit order book are not 'equally distributed' on all price points. Thus, assuming this scenario ex ante seems undesirable for the interpretation of the results. Consequently, I do not assume any strategic order submission behavior but emphasize that the behavioral biases causing order submissions to depend on the number preferences are not an attribute of a specific investment (trading) style.

The bid groups 'bid rises to integer (5 cent)', 'bid rises above integer (5 cent)', and 'bid falls while staying above integer (5 cent)' are constructed in the same manner. Note that within the overall classification not every trade must belong to one group.

After trades have been flagged by the introduced classification, regression models employing different dependent variables are estimated to test the difference between integer and 5 cent groups. Trade direction coded as 1 for a buy and 0 for a sell is used in a logistic regression. Signed turnover (negative for sell turnover) and signed number of shares traded are applied in two multivariate regressions which are estimated by maximum-likelihood. In all three cases the general regression equation is defined as

$$DepVar = \alpha + \sum_{i=1}^{6} \left(\beta_i * int_i + \gamma_i * fiveC_i \right) + \sum controls, \tag{4.5}$$

where int_i and $fiveC_i$ denote the six integer groups and the six five cent groups, respectively. The regression includes control variables for price level, trade size, stock, year, and penny-endings. Controls for penny-endings, i. e., whether a trade price ends on 1,2,...,9, are used to rule out the effect that in case of 'ask falls' groups, for instance, 9 cent endings are generally more preferred than 4 cent endings and therefore would dilute implications regarding the three types of groups ('falls to', 'falls below', 'rises while staying below').

Additionally to BHJ's regression, I use controls for the direction of the previous three trades. These control variables are used to extract the auto-correlation in orderflows, and particularly in the trade direction, which is usually observed in empirical studies (cf. Hasbrouck, 1988; Chung et al., 2005, among others). Assuming there is an independent order flow of, say, human investors who tend to have round number biases, then differences should become larger because of other traders relying on information about the orderflow or because of traders who split large orders. Auto-correlated orderflow of marketable orders basically increases absolute values of imbalances given that the available order book depth is large enough and of similar size on the bid and ask side. Controlling for previous trades does not alter the significance of any difference and therefore does not change the conclusion from the regression results.

Table 4.4 shows the difference of the regression estimates between the integer and 5 cent groups, whereby the significance is verified through Wald tests. The results are in line with the NYSE results of BHJ. Large differences in buy-sell imbalance measures mainly occur for the 'ask falls to integer' and 'bid rises to integer' groups. The other ask (bid) groups also predict excess buying (selling), but are only a fraction of the size of the 'falls (rises) to integer' group. So more buys (sells) are triggered after the ask (bid) falls (rises) to an integer. These trades must not necessarily take place on the exact round number. For example if the 'ask falls to integer' trigger is activated and the size of the next marketable buy order exceeds the quoted size, a buy below the round number takes place. Because the threshold trigger effect would additionally require large differences in the 'ask falls below' and 'bid rises above' groups, it can be concluded that unconditional buy-sell imbalances are mainly driven by cluster undercutting behavior.

TABLE 4.4: **Regression Models with Quote Path Indicators.** This tables shows results from regression models of trade direction, signed turnover, and shares traded. Quote path indicators are defined by the preceded quote development of trades on integer and 5 cent price levels. The regression equation is $DepVar = \alpha + \sum_{i=1}^{6} \left(\beta_i * int_i + \gamma_i * fiveC_i\right) + \sum controls$. The first column shows a logistic regression using a buy-sell indicator (1 for buy and 0 for a sell) as dependent variable. The second and third column report the results from (signed) turnover, and (signed) shares, respectively, as dependent variables. Controls include fixed effects for stock and year as well as dummies for penny-endings (0 to 9) and the trade direction of the previous trade. The model of trade direction applies turnover and shares traded as additional control variables. All regressions are estimated by maximum likelihood techniques. The table reports differences in coefficients between the integer and 5-cent groups for each dependent variable. P-values for coefficient differences are obtained from Wald tests. The sample contains trades on Xetra in DAX30 stocks from January 2009 to December 2013.

	Trade Direction		Signed Turnover		Shares traded (signed)	
	Estimate diff.	p-value	Estimate diff.	p-value	Estimate diff.	p-value
Ask falls below integer- Ask falls below nickel	0.0279	<0.0001	597.03	0.0070	14.5414	0.0796
Ask rises while staying below integer- Ask rises while staying below nickel	0.0389	<0.0001	581.55	<0.0001	21.8824	0.0007
Ask falls to integer- Ask falls to nickel	0.2326	<0.0001	4366.15	<0.0001	124.0131	0.0033
Bid rises to integer- Bid rises to nickel	−0.2316	<0.0001	−2214.47	<0.0001	−11.5586	0.0146
Bid rises above integer- Bid rises above nickel	−0.0199	<0.0001	−1030.00	0.0020	−30.0041	0.0090
Bid falls while staying above integer- Bid falls while staying above nickel	−0.0390	<0.0001	−1144.58	<0.0001	−23.1492	0.0072

4.5 Determinants of Round Number Effects

The last section has shown that buy-sell imbalances around round numbers are present in the German market as well, but exhibit different local characteristics in comparison to the U.S. This section assesses Research Question 3b. Therefore, I extend the analyses and the methodology of BHJ to give a more precise understanding of the observed effects.

4.5.1 Price Level and Tick Size

For the main analysis in the previous section, trades within a price range from EUR 2 to EUR 100 are used and as such the results represent an average of round number effects within this range. Since cluster undercutting is the main driver of buy-sell imbalances around round numbers, the size of clusters (i. e., the relative available depth) should be directly related to the (absolute) size of the buy-sell imbalances.

Harris (1991) argues that price clustering is induced by relatively smaller negotiation costs and finds that clustering increases with price level. The relative error of the potentially imprecise estimation of prices becomes smaller for higher prices given the minimum price change (tick size) remains the same. Ohta (2006) and Chiao and Wang (2009) confirm this relation for other markets and time periods.

An application of the methodology of the previous section to a subsample including trades between EUR 50 and EUR 100 confirms the assumption of larger buy-sell imbalances for higher stock prices. The regression is similar to (4.4), but includes dummies for year and stock. The regression equation becomes

$$Imbalance = \sum_{i=1}^{10} \beta_i * centdummy_i + \sum controls, \tag{4.6}$$

where the ten cent dummy groups are according to the German order of preference (compare Table 4.3). The inclusion of stock-year dummies allows the means of buy-sell imbalances to vary among stocks and years, which addresses the fact that stocks can have varying money in- and outflows from a liquidity demander perspective. In this sense, the model is more meaningful as it does not produce significant coefficients due to imbalances of stocks which deviate strongly from the market imbalance in some cent group, i. e., the unweighted average of buy-sell imbalance of all stock, but do not significantly deviate from their own average. Using these controls in the regressions of Section 4.4.1 does not change the drawn conclusions and for this reason additional tables are omitted.

TABLE 4.5: **Buy-sell Ratios Regressed on Alternative Cent Dummies**. The buy-sell imbalances of liquidity demanders stock are regressed on dummies for cent amount groups (see column 1) which are defined according to the available Euro coins. The general regression equation is $Imba = \alpha + \sum \beta_i * centdummy_i + FixedEffects,\ i = 1, 2, ..., 10$. The model is estimated on a subsample which contains trades between EUR 50 and EUR 100 exclusively. Standard errors of the coefficient estimates are reported in parentheses. *,**, and *** denote significance on the 5%, 1%, and 0.1% level.

	Imbalance		
	Buy/Sell Orders	Buy/Sell Turnover	Shares Bought/Sold
Intercept	0.026	0.0141***	0.1171***
	(0.0141)	(0.0236)	(0.0233)
Below Integers (.99)	0.2575***	0.0187***	0.379***
	(0.0187)	(0.0509)	(0.052)
Above Integers (.01)	-0.2612***	0.0208***	-0.3416***
	(0.0208)	(0.0414)	(0.0412)
Below Half-Euro (.49)	0.1915***	0.0171***	0.2247***
	(0.0171)	(0.0414)	(0.0414)
Above Half-Euro (.51)	-0.2011***	0.0181***	-0.1798***
	(0.0181)	(0.0398)	(0.0398)
Below 20-cents (.19, .39, .59, .79)	0.1226***	0.0062***	0.1526***
	(0.0062)	(0.0218)	(0.0218)
Above 20-cents (.21, .41, .61, .81)	-0.122***	0.0062***	-0.1641***
	(0.0062)	(0.0258)	(0.0257)
Below 10-cents (.09, .29, .69, .89)	0.1165***	0.0057***	0.1173***
	(0.0057)	(0.022)	(0.0221)
Above 10-cents (.11, .31, .71, .91)	-0.1228***	0.0061***	-0.1476***
	(0.0061)	(0.0229)	(0.023)
Below 5-cents(.04, .14, .24, .34, .44,	0.0626***	0.0035**	0.0435**
.54, .64, .74, .85, .94)	(0.0035)	(0.0149)	(0.0149)
Above 5-cents(.06, .16, .26, .36, .46,	-0.0674***	0.0034***	-0.09***
.56, .66, .76, .86, .96)	(0.0034)	(0.015)	(0.015)
Controls	Stock, Year	Stock, Year	Stock, Year

Results for the subsample are reported in Table 4.5. Coefficients are statistically significant and confirm the main results. However, they are absolutely larger than for the complete sample confirming the assumption that the focus on round numbers increases in price level. The smaller relative error from an imprecise estimation of a fair price seems to move the attention to rounder numbers, since the effects in the integer and half-Euro groups increase most.

When discussing differences in price levels, the question arises whether the tick size rule has an impact on the results. For the subsample of trades between EUR 50 and EUR 100 a minimum tick size of 1 cent applies during the whole sample period. The new rule defines a step-wise tick size schedule and was introduced at the beginning of 2010. For stocks traded between EUR 10 and EUR 50 the minimum tick size reduces to 0.5 cent, and to 0.1 cent for stocks below EUR 10, respectively.

Chiao and Wang (2009) find that price clustering in the Taiwanese stock market increases with absolutely smaller tick sizes. For human investors small tick sizes might be irrelevant because their ability to estimate the fair value is not precise enough to distinguish between very small price differences. Furthermore, it might be more complicated for human investors to use sub-cent values for limit order submission which is also in line with the negotiation argument by Harris (1991). Thus, it seems probable that orders of human investors still tend to cluster on round numbers, whereas orders of sophisticated market participants such as algorithmic traders could be distributed on more price points. This would increase the relative clustering, i. e., differences in transaction volume as well as in offered depth between adjacent price points might increase, in particular if one price level was a cluster under the old rule.

To detect changes in trades of stocks which are affected by the new tick size rule, I use an extended conditional analysis. Since implications are the same for all dependent variables used in regressions (4.5), I focus on trade direction. For the following regression only the years 2009 and 2010 are used, i. e., one year before and after the introduction. I adopt the model to represent an event study approach. The regression equation becomes

$$\begin{aligned} BuySell = &\sum_{i=1}^{6}(\beta_i^{(1)} * int_i + \beta_i^{(2)} * int_i * dummy2010 + \beta_i^{(3)} * int_i * tick \\ &+ \beta_i^{(4)} * int_i * tick * dummy2010) + \sum_{j=1}^{6}(\gamma_j^{(1)} fiveC_j * [...]) + \sum controls, \end{aligned}$$

where $dummy2010$ indicates the year 2010, int_i and $fiveC_i$ denote dummies for the six integer and 5-cent groups, and $tick$ is a dummy variable which equals one for price levels having a change in tick size and zero else. The term $\sum_{j=1}^{6} \gamma_j^{(1)} fiveC_j * [...]$ abbreviates the sum of the five-cent groups which is defined analogously to the integer terms.

Table 4.6 shows the difference between the coefficients of the integer and 5-cent groups based on the above logistic regression. To check the significance of these differences, I apply Wald tests from which the reported p-values result. First of all, the interpretation of the regression results remain unchanged compared to the complete sample and the original regression specification. Consequently, it is convenient to interpret the falls (rises) to integer and 5-cent differences to detect a possible impact of the new tick size rule.

Confirming the last subsection, the positive influence of the price level on the effects is found as well. The baseline effect $\beta_i^{(1)} - \gamma_i^{(1)}$ refers to trades in 2009 between EUR 50 and EUR 100. The differences $\beta_i^{(3)} - \gamma_i^{(3)}$ which distinguish the two tick classes are consistently opposite to the baseline effect $\beta_i^{(1)} - \gamma_i^{(1)}$. This means, stocks which are affected by the new tick size in 2010 generally exhibit smaller imbalances as their price level is lower. The negative estimates are not surprising since stocks which are affected by the new tick size are low-priced and therefore tend to exhibit smaller round number effects as shown above. The differences $\beta_i^{(2)} - \gamma_i^{(2)}$ reported in column 'Dummy 2010' are opposed to the baseline effect indicating that round number effects weakened considerably from 2009 to 2010. The yearly development of the size of the effects is elaborated in Section 4.5.3.

TABLE 4.6: **The Impact of Tick Size Regimes on Conditional Buy-Sell Imbalances.** The regression models reported in this table are specified as $BuySell = \sum_{i=1}^{6}(\beta_i^{(1)} * int_i + \beta_i^{(2)} * int_i * dummy2010 + \beta_i^{(3)} * int_i * tick + \beta_i^{(4)} * int_i * tick * dummy2010) + \sum_{j=1}^{6}(\gamma_j^{(1)} fiveC_j * [...]) + \sum controls$, where controls include fixed effects for stock and year as well as dummies for penny-endings (0 to 9), turnover, volume, and the trade direction of the previous trade. The table shows differences in coefficient estimates between the integer and 5-cent group with respect to the tick size dummy and the dummy for trades in 2010, as well as their intersection. Column 'No Dummy' shows the baseline effect, i.e. stocks traded between EUR 50 and EUR 100 in 2009. Columns 'Dummy 2010' and 'Tick Size Dummy' measure overall changes in 2010 and the difference of effects in the group of trades between EUR 2 and EUR 50. The column 'Tick Size & 2010' shows the differences in the interaction term which measure the impact of the new tick size regime. P-values for coefficient differences are obtained from Wald tests.

	No Dummy $\beta_i^{(1)} - \gamma_i^{(1)}$		Dummy 2010 $\beta_i^{(2)} - \gamma_i^{(2)}$		Tick Size Dummy $\beta_i^{(3)} - \gamma_i^{(3)}$		Tick Size & 2010 $\beta_i^{(4)} - \gamma_i^{(4)}$	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
Ask falls below integer- Ask falls below nickel	0.0392	<0.0001	−0.0213	<0.0001	−0.0157	0.0004	0.0098	0.0991
Ask rises while staying below integer- Ask rises while staying below nickel	0.0919	<0.0001	−0.0590	<0.0001	−0.0327	<0.0001	0.0436	<0.0001
Ask falls to integer- Ask falls to nickel	0.4368	<0.0001	−0.2100	<0.0001	−0.1432	<0.0001	0.1251	<0.0001
Bid rises to integer- Bid rises to nickel	−0.4399	<0.0001	0.2659	<0.0001	0.1593	<0.0001	−0.2441	<0.0001
Bid rises above integer- Bid rises above nickel	−0.0362	<0.0001	0.0101	0.0459	0.0221	<0.0001	0.0066	0.2716
Bid falls while staying above integer- Bid falls while staying above nickel	−0.0803	<0.0001	0.0270	<0.0001	0.0360	<0.0001	−0.0300	<0.0001

The last column of Table 4.6 lists the differences in coefficients estimates which include an interaction term between tick size and year 2010 dummies. This difference measures changes from 2009 to 2010 within the group of trades that actually are effected by the new tick size rule. The differences are significant and imply stronger round number effects. The overall effect for the EUR 2 to EUR 50 class in 2010 is still weaker than in 2009, but it did not decrease as much as the benchmark group (EUR 50 to EUR 100). However, given a general trend of weakening round number effects over time, the overall effect, i. e., the sum of coefficients, is still decreasing. Hence, to argue the new tick size rule is worrying with respect to limit order clustering and round number effects seems questionable, although the presented model shows an positive effect when it is analyzed isolated.

Running the same regression with Q4/2009 and Q1/2010 in order to reduce the impact of a time trend, the 'Ask falls to' difference $\beta_i^{(4)} - \gamma_i^{(4)}$ is not statistically significant but the corresponding bid group. The latter might partially be a results of the reduced statistical power given the smaller sample size. Explicit results are shown in Appendix A.5. Isolating the effect from the altered tick size on a reduction of round number effects is hard to disentangle from the overall (negative) trend based on this analysis. However, both regression point in the direction that smaller tick sizes increase round number effects, which is in line with Chiao and Wang (2009).

In general, the smaller minimum tick size has led to reduced spreads for stocks below EUR 50. For example, the average time-weighted quoted (half) spreads of the whole sample declined from 6.50bps in 2009 to 3.40bps in 2010 (see Table 4.1). The average effective (half) spread of all trades between EUR 2 and EUR 10 decreased from 5.95bp in 2009 to 3.33bps in 2010 and from 3.42bps to 2.58bps for trades between EUR 10 and EUR 50. This means the reduction in (effective) spreads would not have been possible without a reduction of the minimum tick size (e. g., $2 * 3.33\text{bps} * \text{EUR}10 < \text{EUR}0.01$). However, round number effects within this group of stocks remained the same. So positive effects from the reduced tick size on spreads should outweigh increasing round number effects.

4.5.2 Mid-cap Stocks

This section assesses the relation of market capitalization and round number effects. The fifty MDAX constituents are used to show that round number effects are not an artifact of the thirty German blue chips but of the whole German market. By applying the unconditional analysis on a second set of stocks, the robustness of the main results is confirmed. Figure 4.3 shows the average buy-sell order imbalance for MDAX (solid) and DAX (dashed) stocks. Buy-sell imbalances of MDAX stocks are qualitatively equal, i. e., the same pattern evolves but the imbalances seem to be generally larger. To test for a possible difference, I pool DAX30 and MDAX50 firm-year imbalances and adapt regression (4.6), which results in

$$Imbalance = \sum_{i=1}^{10} \left(\beta_i * centdummy_i + \gamma_i * MDAX * centdummy_i\right) + \sum FixedEff, \tag{4.7}$$

where $FixedEff$ include dummy variables for year and stock.

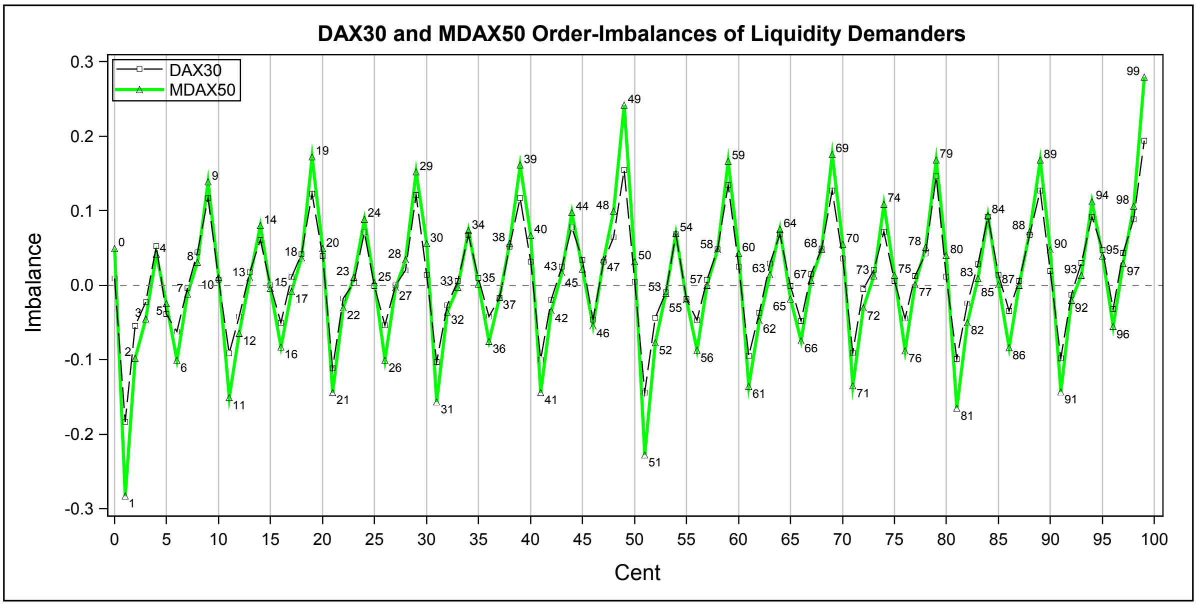

FIGURE 4.3: **DAX30 and MDAX50 Imbalance Measures of Liquidity Demanding Orders on Xetra.** Average buy-sell order imbalance of MDAX50 stocks (solid line) and DAX30 stocks (dashed line) from 2009 to 2013.

The results are reported in Table 4.7. Round number effects are qualitatively the same for MDAX50 stocks as for DAX30 stocks, i. e., the order of roundness reappears equivalently as expected from Figure 4.3. The estimated sign of each coefficient γ_i indicates greater buy-sell imbalances for MDAX50 stocks. In case of buy-sell order imbalances as dependent variable, coefficients are consistently significant on a 0.1% level. The absolute size of coefficient indicate that buy-sell-imbalances are more than 50% larger for MDAX than DAX on almost all levels.

In case of imbalances based on turnover and traded shares, only some round number thresholds are significantly different between MDAX and DAX. This is primarily due to the much higher noise in these variables which increases the coefficients' standard deviation. In order to avoid examining every single threshold, I aggregate the regressions coefficients by summing up all coefficients of 'below' round number dummies and coefficients of 'above' round number dummies multiplied by -1 to be consistent with the hypothesized round number effects. That is, the sums $\sum_{i=1}^{10}(-1)^{i+1}\beta_i$ for the DAX and $\sum_{i=1}^{10}(-1)^{i+1}(\beta_i+\gamma_i)$ for the MDAX constitutes a proxy for the overall magnitude of buy-sell imbalance in the respective sample of stocks.

Calculated from the estimates of the respective regressions, the differences between both groups are 0.8390, 0.6011, and 0.6092 for order, turnover, and traded-shares imbalances, respectively. Wald tests confirm the significance on the 0.1% level for all differences. Thus, round number effects are stronger in the mid-cap index MDAX compared to the large cap stocks in the DAX. During the sample period the average price of trades in DAX stocks is 42.98 and 30.98 for MDAX stocks, respectively (see Table 4.1). According to Section 4.5.1 DAX stocks are expected to exhibit greater imbalances due to the higher price level. Since the differences between MDAX and DAX show the opposite, the results of this sub-section can be considered as conservative.

TABLE 4.7: **Buy-sell Imbalances in DAX30 and MDAX50 Stocks.** This table show results from regression buy-sell imbalance measures of liquidity demanders on cent group dummies which fit to the available Euro coins. To detect differences of round number effects in DAX and MDAX stocks, data from both indices are pooled and the model includes the intersection of the MDAX dummy variable with all cent group dummies. The regression equation becomes $Imba = \sum\left(\beta_i * centdummy_i + \gamma_i * MDAX * centdummy_i\right) + \sum FixedEffects,\ i = 1, 2, ..., 10$. The model uses fixed effects for stock and year. *, **, and *** denotes significance on the 5%, 1%, and 0.1% level. The sample period spans from January 2009 to December 2013.

	Imbalance					
	Buy/Sell Orders		Buy/Sell Turnover		Shares Bought/Sold	
	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Below Integers (.99)	0.2014***	0.0148	0.2874***	0.0275	0.2853***	0.0273
MDAX * Below Integer	0.1186***	0.0222	0.0539	0.0356	0.0539	0.0356
Above Integers (.01)	-0.2102***	0.0150	-0.2807***	0.0275	-0.2805***	0.0274
MDAX * Above Integer	-0.1344***	0.0212	-0.0703*	0.0338	-0.0656	0.0337
Below Half-Euro (.49)	0.1607***	0.0129	0.2040***	0.0243	0.2059***	0.0239
MDAX * Below Half-Euro	0.1144***	0.0185	0.0979**	0.0306	0.0992**	0.0302
Above Half-Euro (.51)	-0.1689***	0.0125	-0.1718***	0.0268	-0.1657***	0.0272
MDAX * Above Half-Euro	-0.1200***	0.0187	-0.1389***	0.0331	-0.1431***	0.0334
Below 20-Cents (.19, .39, .59, .79)	0.1254***	0.0045	0.1430***	0.0137	0.1443***	0.0137
MDAX * Below 20-Cents	0.0648***	0.0071	0.0480**	0.0172	0.0480**	0.0172
Above 20-Cents (.21, .41, .61, .81)	-0.1156***	0.0043	-0.1462***	0.014	-0.1459***	0.0139
MDAX * Above 20-Cents	-0.0766***	0.0066	-0.0682***	0.0171	-0.0677***	0.0168
Below 10-Cents (.09, .29, .69, .89)	0.1163***	0.0040	0.1260***	0.0121	0.1258***	0.0120
MDAX * Below 10-Cents	0.0606***	0.0066	0.0521***	0.0157	0.0558***	0.0155
Above 10-Cents (.11, .31, .71, .91)	-0.1114***	0.0042	-0.1386***	0.0132	-0.1377***	0.0131
MDAX * Above 10-Cents	-0.0797***	0.0066	-0.0466**	0.0166	-0.0447**	0.0165
Below 5-Cents (.04, .14, ?)	0.0616***	0.0024	0.0548***	0.0083	0.0554***	0.0082
MDAX * Below 5-Cents	0.0217***	0.0039	0.0215*	0.0104	0.0246*	0.0103
Above 5-Cents (.06, .16, ?)	-0.0588***	0.0023	-0.0807***	0.0083	-0.0795***	0.0082
MDAX * Above 5-Cents	-0.0521***	0.0039	-0.0349***	0.0104	-0.0338**	0.0103

As an additional robustness check, I apply a Tobit regression to model absolute imbalances. The model specification is basically equivalent to (4.7) but it includes the yearly average price for each stock as an independent variable, which should be positively related to the absolute imbalance measures. The regression results confirm the hypothesized relationship between round number effects and price level, but the differences between DAX and MDAX stocks remain highly significant. Estimation results of the Tobit regression are reported in Table A.4 of Appendix A.2.

Several reasons for the larger effects in the index of mid-cap stocks seem probable. First, because there is less volume in MDAX stocks and spreads are higher, a relation between round number effects and liquidity could be imaginable. With respect to order clustering it seems not sufficient to just increase overall depth, for instance, as long as the additional limit orders have basically the same characteristics. That is, to reduce limit order clustering and undercutting the additional liquidity would have to balance the existing liquidity assuming the characteristics of prevailing liquidity remain stable over time. Second, the proportion of algorithmic trading in the mid-cap index is smaller which could also be linked to lesser liquidity. Assuming that algorithmic traders have generally no tendency to focus on any round number and no additional costs from using small price increments, the strength of round number effects should be correlated with the ratio of human and algorithmic traders in a market segment.

4.5.3 Time Trends in Round Number Effects

Empirical market microstructure literature shows that financial markets have become more efficient and more liquid over the last decades. More efficient market systems and participants such as algorithmic traders are primary reasons for this development. As hypothesized in Section 4.2, the increasing share of algorithmic traders, who I assume to be unaffected by cognitive number biases, could possibly result in weakening round number effects. Therefore the development of the effect over the sample period is investigated.

In Section 4.5.1 the conditional analysis of trades already revealed smaller coefficients for the 'ask (bid) falls (rises) to integer' group in 2010 than in 2009. Another approach to detect time trends in buy-sell imbalances is to allow multilevel slopes and intercepts in regression (4.6). Then the regression equation becomes

$$\text{Imbalance} = \sum_{j=1}^{4}\sum_{i=1}^{10}\beta_{ij} * \text{centdummy}_i * year_j + \sum_{j=1}^{4}\sum_{k}\text{stock}_k * year_j. \tag{4.8}$$

I estimate six regressions based on the DAX30 and MDAX50 samples (separately) and the three imbalance measures as defined in Section 4.4.1. Table 4.8 presents the absolute sums of coefficients for each year. Furthermore it shows p-values from Wald tests which verify the significance of differences between the sums of coefficients of consecutive years. Formally the specified Wald test assesses the hypotheses $\sum_{i=1}^{10}\left(\beta_{i,j+1} - \beta_{i,j}\right) = 0,\ j = 1,2,3$, where $\beta_{i,j}$ are maximum-likelihood estimates of the model parameters.

In case of the DAX30 sample, the sum of absolute coefficients estimated by the order imbalance regression is 0.6539 smaller in 2010 than in 2009 and this difference is statistically significant (p-value < 0.0001). The declining trend holds during the following three years as well, which means round number effects have become gradually weaker over the sample period, although prices of DAX (MDAX) stocks rise from a yearly average price of 36.06 (26.28) in 2009 to 47.50 (39.62) in 2013. Since Section 4.5.1 shows that round number effects increase in price level, the declining trend can be regarded as conservative. The results from the turnover and traded shares imbalance measures of DAX30 stocks are similar, except for the fact that there is no significant difference between 2011 and 2012 anymore. A reason might be the much higher variability inherent in (signed) turnover and traded shares compared to the mere number of buys and sells.

Interestingly, in case of the MDAX50 data, there is no significant drop in the absolute sum of coefficients from 2009 to 2010, but during the following years. To some extent, this should be related to an increasing price level in these years. All stocks have been traded on the same system (i. e., Xetra), thus technological differences affecting trading can be excluded. A reason might be that algorithmic traders or other efficiency-improving market participants first focused on large-cap stocks and turned their attention on mid-cap stocks in the following years.

TABLE 4.8: **Analysis of Time Trends in Buy-sell Imbalances on Xetra.** The table shows the sum of absolute coefficients of all cent dummies per year estimated from the regression model $Imbalance = \sum_{i=1}^{10}\sum_{j=1}^{5}\beta_{i,j} * centdummy_i * year_j + \sum_k \sum_{j=1}^{5} stock_k * year_j$. The three introduced imbalance measures are employed as dependent variables for DAX30 data (Panel A) and MDAX50 data (Panel B). The significance of the year-to-year difference of the coefficient sums is tested via a Wald test regarding the hypothesis $\sum_{i=1}^{10}\beta_{i,j+1} - \beta_{i,j} = 0, j = 1, ..., 4$. P-values refer to the year-to-year Wald test.

Panel A: DAX	Order Imbalance			Turnover Imbalance			Shares Imbalance		
Year	Sum of Coeff.	Δ yr/yr	p-value	Sum of Coeff.	Δ yr/yr	p-value	Sum of Coeff.	Δ yr/yr	p-value
2009	2.1468	-	-	2.3881		-	2.3537	-	-
2010	1.4929	−0.6539	<0.0001	1.8087	−0.5794	0.0008	1.8074	−0.5462	0.0110
2011	1.2128	−0.2801	<0.0001	1.3806	−0.4281	0.0128	1.3681	−0.4393	0.0086
2012	0.9724	−0.2404	<0.0001	1.5071	0.1265	0.4701	1.5184	0.1503	0.3847
2013	0.6948	−0.2776	<0.0001	0.9801	−0.5270	0.0032	0.9814	−0.5370	0.0027
Panel B: MDAX									
2009	2.7275	-	-	2.7502	-	-	2.7505	-	-
2010	2.6986	−0.0289	0.6921	2.7772	0.0269	0.8433	2.7842	0.0337	0.8027
2011	2.2421	−0.4565	<0.0001	2.1919	−0.5853	<0.0001	2.1832	−0.6010	<0.0001
2012	1.5952	−0.6468	<0.0001	1.8437	−0.3482	0.0081	1.8375	−0.3457	0.0080
2013	1.6405	0.0453	0.5266	1.7993	−0.0444	0.7391	1.7930	−0.0445	0.7366

A similar extension of the conditional analysis of Section 4.4.2 leads to the same conclusion of decreasing round number effects over the years. For example, the logistic regression modeling the occurrence of a buy after the ask price has fallen to an integer or to a 5 cent level, respectively, shows constantly decreasing differences in these groups over the years.

Overall, the identified decrease of buy-sell imbalances can be interpreted as a higher level of market efficiency. There are several causes which might play a role in this development. First of all, improvements in information systems of Xetra and its market participants were accompanied by improved market liquidity, such as smaller spreads, increased depth. Second, sophisticated market participants could actively exploit round number anomalies and thereby weaken the effects. If market participants who run market making strategies identify large clusters and imbalances in liquidity supply and demand on some price levels, they could adjust their liquidity supplying strategy by increasing liquidity provision on the side of the book with less depth and thereby round number effects could consequently weaken. On the other hand, human investors might have become aware of their round number biases and, thus, they try to avoid placing orders on or around round numbers.

4.6 The Case of Retail Investors at the Stuttgart Stock Exchange

The latter section has shown that round number effects have gradually weakened over the observation period. Several possible reasons have been put forward to explain these results. However, the insights from the Xetra Times & Sales data is limited. There is no information on who is trading and, more particular, whether an order is submitted by an algorithmic trading system or by a human investor.

The important feature of the data provided by Stuttgart Stock Exchange is the certainty that orders and transactions are on behalf of human investors because algorithmic trading interfaces or co-locations are not permitted. A disadvantage of the data is the relatively small trading volume, which is about 1 percent compared to Xetra (see Table 4.1).

Furthermore, the mechanism of stock trading at Stuttgart Stock Exchange is distinct from Xetra. The hybrid trading system combines a standard limit order book with market makers (so-called quality liquidity provider) who actively improve market quality. They spend liquidity when client orders could be executed given Xetra bid or ask quotes although there is no matching order in the limit order book at the Stuttgart Stock Exchange. This so-called reference market principle ensures that (retail) clients obtain prices which are as least as good as on Xetra up to a given trade size. Consequently, market orders processed by this mechanism become independent from standing limit orders in the book, i. e., imbalances in supply and demand of traders are automatically resolved by market makers. The described process usually runs automatically without any active interventions by human market makers as long as incoming orders are within predefined parameters.

The market structure of stock trading at the Stuttgart Stock Exchange has some implications for the presented analysis of round number effects. First of all, results are not directly comparable to results from Xetra due to the mentioned differences. The reference market principle and the low volume makes the contribution to price discovery of stock trading in Stuttgart become negligible. Theoretically, market makers who balance their inventories could have an impact on Xetra prices, but the potential effect should be minimal because of the small volume.

The interesting aspect regarding the analysis of round number effects is that liquidity demand and supply are detached by market makers who buy and sell according to predetermined conditions, i. e., bid and ask quotes of the reference market Xetra. Thus, different patterns in executed limit orders and marketable orders are possible, in contrast to a pure limit order book market where these orders will always match. For the present analysis of round number effects it is possible to separately assess which patterns occur in each order type and how these pattern differ.

There are considerable differences in the patterns of buy-sell imbalances between limit and marketable orders by retail investors. Figure 4.4 contrasts the averages of buys-sell order imbalance measure based liquidity demanding orders, liquidity demanding orders without stop-orders and other exotic order-types and, analogously Figure 4.5 depicts liquidity supplying orders. In all three cases investors place more buy than sell orders over the observation period as the positive overall buy-sell imbalances (dashed

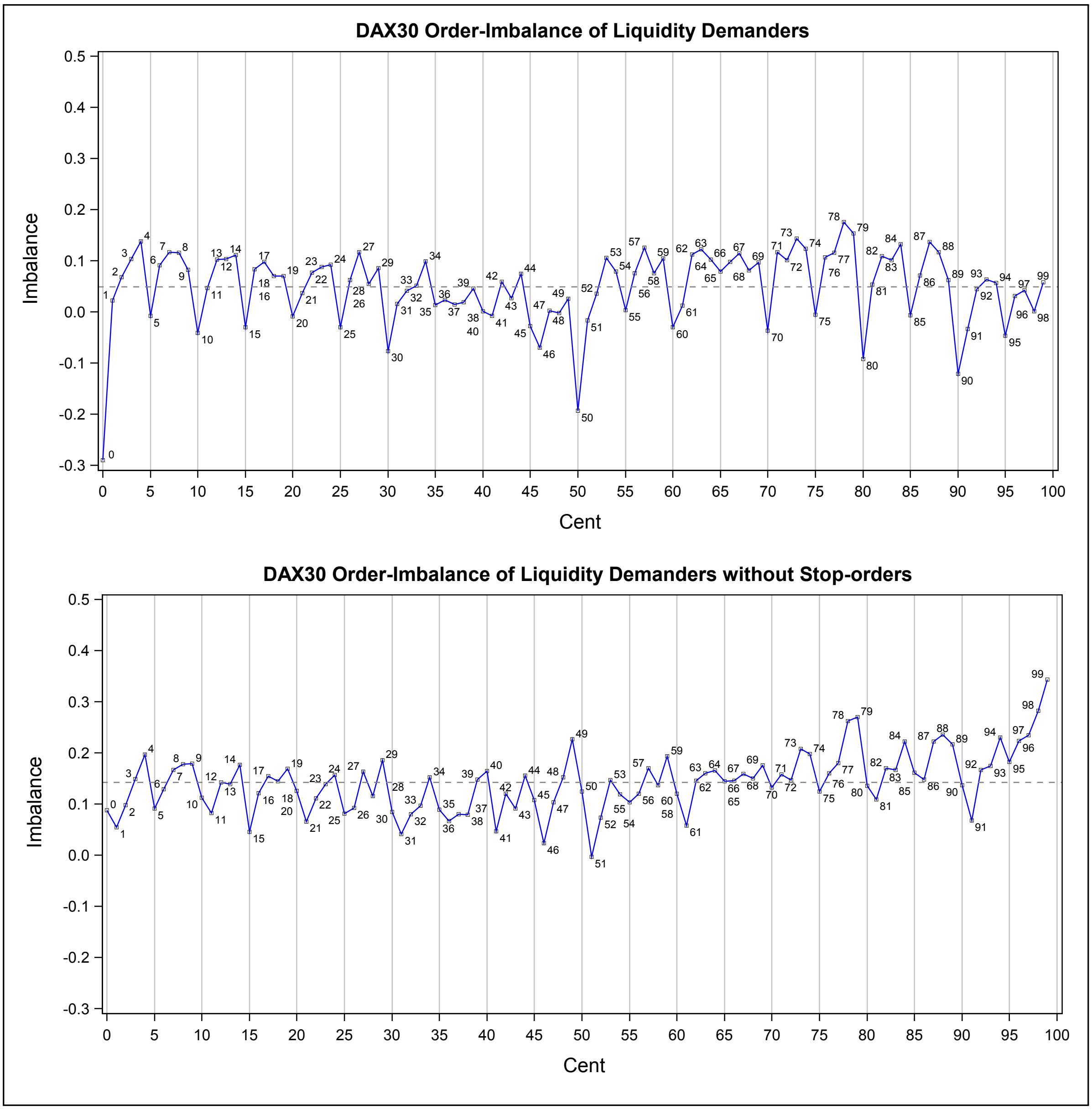

FIGURE 4.4: **Imbalances of Liquidity Demanding Orders at the Stuttgart Stock Exchange.** The upper plot shows average buy-sell order imbalances of liquidity demanding orders in DAX30 stocks at Stuttgart Stock Exchange from April 2009 to December 2013. For the bottom plot stop-orders and other exotic order types are excluded. The dashed horizontal line depicts the respective average buy-sell imbalance.

lines) show. On the first plot, a large surplus of sells exactly on round numbers is apparent. This is mainly due to stop-loss orders which are extremely popular among retail investors. Because of their functionality stop-loss orders have to be treated as

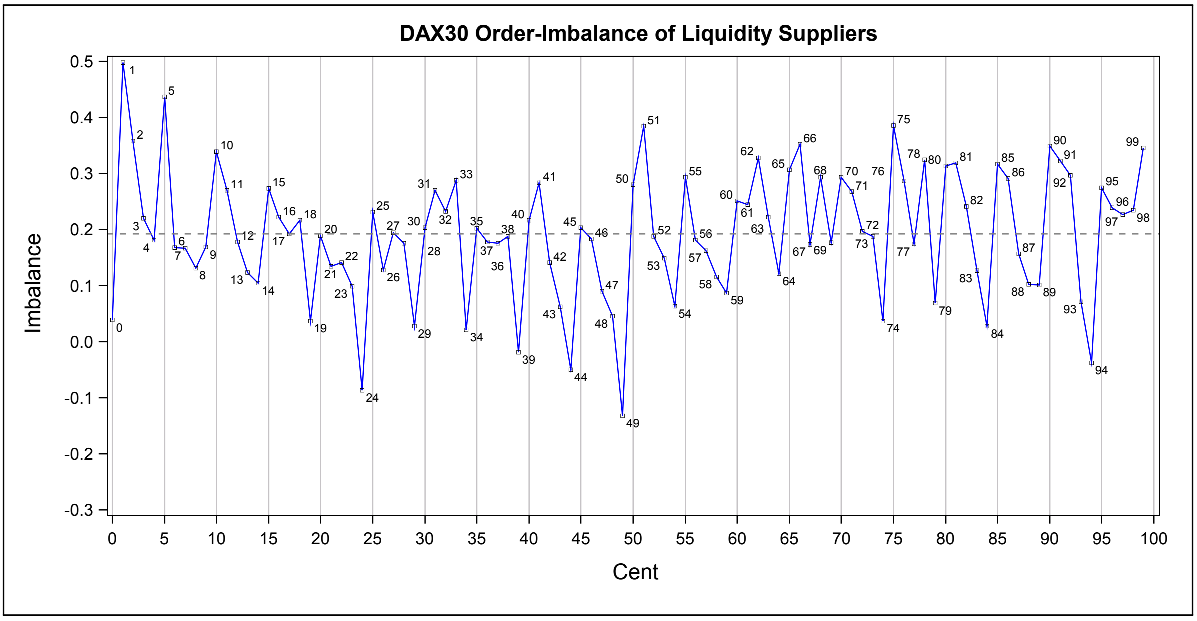

FIGURE 4.5: **Imbalances of Liquidity Demanding Orders at the Stuttgart Stock Exchange.** The plot shows average buy-sell order imbalances of executed liquidity demanding orders in DAX30 stocks at Stuttgart Stock Exchange from April 2009 to December 2013. The dashed horizontal line depicts the average buy-sell imbalance.

liquidity demanding orders. The necessity to enter a stop price makes this order type susceptible for round number biases of the order submitter. Since stop-loss orders are much more common than stop-buy[2] orders, the sell side turns out to be very dominant for all round price levels where stop orders are typically placed.

Excluding stop-orders (bottom plot of Figure 4.4) removes the spikes on round numbers, but still there is a less clear pattern as expected from Xetra data (see Figure 4.2 & 4.3). Order imbalances show a much noisier behavior and relatively small deviations from the mean suggesting that retail investors who submit marketable orders have a weaker propensity to base their market order submission on cent endings or other number references.

On the other hand, buy-sell imbalances of marketable order can only lack an explicit pattern if the demand is not restricted by the supply side, which is the case at Stuttgart Stock Exchange except the applied reference market principle. Assuming a sufficiently large number of randomly incoming orders which are equally distributed over time, the

[2]Also referred to as start-buy orders.

resulting patterns of buy-sell imbalances at the Stuttgart Stock Exchange should become similar to Xetra since market makers set their prices in accordance to Xetra. Due to the small number of trades a considerable amount of noise should bias the actual pattern. Yet despite the mentioned relation between the exchanges the observed pattern is much weaker than on Xetra, so it is conservative to argue there is no particularly pronounced round number bias in market orders executed at Stuttgart Stock Exchange.

Figure 4.5 shows buy-sell imbalances based on limit prices of all executed, non-marketable limit orders. Due to diluting effects on the actual transaction price stemming from the reference market principle of Stuttgart Stock Exchange, the corresponding limit price is considered. Similar to the liquidity demander plot, the line is noisier than for Xetra, which is presumably related to the much smaller number of observations. The typical pattern – in this case more buys above round numbers and more sells below – is apparent for the limit order data and the relatively large fluctuations suggest that limit orders are considerably biased. In contrast to investors on Xetra, retail investors at Stuttgart Stock Exchange place more buy orders on multiples of five and ten (compared to the overall average) except on the integer price level which tends to be more preferred for sells.

For both, liquidity demanding and supplying order, the 99 cent prices seem to be special for human investors at the Stuttgart Stock Exchange. Buying at prices having 99 cent endings is quite intense in both cases. In case of demanding orders the imbalance has the expected tendency but is much stronger than the other price levels. For liquidity supplying orders a surplus of sells is expected but the opposite appears, i. e., more buys than sells. This is evidence for the left-digit effect, i. e., retail investors perceive the smaller left-digit number associated with the 99 cent price level as a signal to buy.

The visual conjecture is formalized by regression models of type (4.6). The model is estimated for the limit order sample and the sample of marketable orders without stop-loss, respectively. The results of the order imbalance measures are printed in Table 4.9. For liquidity demanding orders coefficient estimates are relatively small and only four out of ten levels are significant on a 1% level. The below integer exhibits the absolutely largest value in this model, which is indication for the left-digit effect for marketable orders. The other significant levels are above integer, half-Euro, and 20-cents which exhibit increased selling behavior. However, the lack of a consistent pattern for all (most of) the considered levels as on Xetra seem to support the result of previous sections, i. e., round number effects tend to be induced by undercutting behavior of limit order submitter and not by investors using market orders. This fits the intuition from a theoretical perspective in the sense that marketable orders are preferred when immediacy is the main objective of the investor. Then considerations about the current or realized price of the stock is of subordinate importance. Since about 80 percent of marketable orders are market orders, no limit price must be specified for the order. Thus, the most obvious way to convey round number biases of investors into trade prices is removed.

TABLE 4.9: **Regression Model of Buy-sell Imbalance Ratios at Stuttgart Stock Exchange.** The table shows regression results from the sample of executed limit orders and the sample of marketable orders in DAX30 stocks at the Stuttgart Stock Exchange. The sample period spans from April 2009 to December 2013. The regression equation is defined as $Imba = \sum \beta_i * centdummy_i + \sum FixedEffects$, where $i = 1, 2, ..., 10$, and $FixedEffects$ denote stock and year dummies. *, **, and *** denote significance on the 5%, 1%, and 0.1% level.

	Liquidity Suppliers Buy/Sell Orders		Liquidity Demanders Buy/Sell Orders	
	Estimate	Std. Error	Estimate	Std. Error
Below Integers (.99)	0.0577	0.0608	0.1822***	0.0446
Above Integers (.01)	0.2939***	0.0633	-0.1411**	0.0439
Below Half-Euro (.49)	-0.3469***	0.0633	0.0703	0.0439
Above Half-Euro (.51)	0.2273***	0.0662	-0.1456**	0.0443
Below 20-Cents (.19, .39, .59, .79)	-0.1633***	0.0326	0.0379	0.0227
Above 20-Cents (.21, .41, .61, .81)	-0.0145	0.0335	-0.0942***	0.0227
Below 10-Cents (.09, .29, .69, .89)	-0.1129***	0.0337	0.0519*	0.0225
Above 10-Cents (.11, .31, .71, .91)	0.0456	0.0338	-0.0425	0.0227
Below 5-Cents(.04, .14, .24, .34, .44, .54, .64, .74, .85, .94)	-0.1868***	0.022	0.0198	0.0149
Above 5-Cents(.06, .16, .26, .36, .46,	0.0084	0.0218	-0.0056	0.0149

Regression results from liquidity supplying orders show more pronounced round number effects in buy-sell imbalances, but not all levels exhibit significant estimate as in case of the Xetra data. Interestingly, the 'below integers' estimate, which is expected to be the largest among the below round number variables, is not significant and close to zero. This means that for retail investors 99 cent prices are comparably attractive for buy and sell orders alike. On the other hand, the left-digit effect seems to play a role for the 'below integers' level as it is the only dummy which means a change in the left digit. Thus, setting a limit price for a (non-marketable) limit buy order exactly below the integer might be perceived as cheaper, which is not the case for limit sell orders for which the integer price point (.00) implies a changing left digit. The average buy-sell imbalance of integer price levels is slightly positive, but it is about 0.15 below the overall buy-sell imbalance of 0.19 (see Figure 4.5. So the integer price level also emphasizes a left-digit effect.

TABLE 4.10: **Analysis of Time Trends in Buy-sell Imbalances at Stuttgart Stock Exchange**. The table shows results from regression models analyzing changes in buy-sell imbalances over time. The model is estimated for the sample of limit orders (Panel A) and marketable orders (Panel B) in DAX30 stocks executed at the Stuttgart Stock Exchange. The sample period spans from April 2009 to December 2013. Due to the limited sample size and data restrictions, a shift between first and second half of the sample period is considered. Within these two periods trades are aggregated to obtain a meaningful number of observations for each cent amount per stock. The regression equation is defined as $Imbalance = \sum_{j=1}^{2}\sum_{i=1}^{10}\beta_i * centdummy_i * period_j + \sum_k \sum_{j=1}^{2} stock_k * period_j$. *, **, and *** denotes significance on the 5%, 1%, and 0.1% level of the period effect $\sum_{i=1}^{10} -1^i \beta_{i,j},\ j = 1,2$, based on a Wald test. To test the differences between periods, the hypothesis $\sum_{i=1}^{10} \beta_{i,j+1} - \beta_{i,j} = 0,\ j = 1,2$ is tested by means of a Wald test. P-values from this test are shown in the last column.

Panel A: Liquidity Supplier Period	Sum of coefficients	Δyr/yr	p-value
2009/04 - 2011/06	1.2496***	-	-
2011/07 - 2013/12	1.7051***	0.4555	0.5368
Panel B: Liquidity Demander			
2009/04 - 2011/06	0.8631***	-	-
2011/07 - 2013/12	0.7190***	−0.1441	0.3862

As shown in Section 4.5.3, unconditional buy-sell imbalances decrease over the sample period and several possible explanations for the finding were discussed. Based on the trade data from Stuttgart Stock Exchange, a potential relation to human investors who diminish their round number biases can be tested. Therefore, an extended regression similar to (4.8) is applied. Due to the much smaller sample size and the missing data for Q1/2009, there are not enough orders to obtain a reliable yearly buy-sell imbalance of each cent amount of every stock. Because of these limitations, I run the regression model with pooled data for the first and second half of the sample period. Regression results are shown in Table 4.10.

Both regressions indicate that human investors at Stuttgart Stock Exchange keep their round number biases over the years. For liquidity demanders the overall effect is decreasing, but not on a statistically significant level. In contrast, coefficient estimates for liquidity suppliers slightly increase, which is not significant, though. So in both cases round number effects remain stable over time, i. e., effects development differently on Stuttgart Stock Exchange and Xetra where a decrease in round number effects is observed[3]. This result contradicts the hypothesized explanation of decreasing buy-sell imbalances due to retail investors becoming aware of their round number biases. Hence, it supports the explanation that improved market efficiency and an increased share of sophisticated traders on Xetra is responsible for the decrease.

4.7 Summary and Conclusion

Round number effects influence trading in the German stock market (Research Question 3). In this chapter, I have analyzed trading data from Xetra and find excessive buy-sell-imbalances around round numbers to be apparent in Germany, but the order of roundness deviates from the American market (NYSE) as found by Bhattacharya et al. (2012). In particular, there is no quarter effect in Germany. Instead, 20-cent price levels tend to exhibit larger imbalances (Research Question 3a). Although the reason for differences in the particular cognitive reference points cannot be identified with certainty, an habituation effect of market participants regarding the local currency and historic trading conditions (e. g., eighth and sixteenth tick sizes in the U.S.) seems natural.

Further, I analyze what drives buy-sell-imbalances and how they develop over time (Research Question 3b). As expected, higher prices levels are associated with larger buy-sell imbalances around round numbers. Likewise, smaller tick size lead to stronger round number effects as limit orders can be distributed over more price steps. However,

[3]Using an regression specification that applies Xetra data that is pooled over two years, results in the same conclusion as on a yearly basis.

the latter is superimposed by the overall negative trend in round number effects which is stable over the sample period.

Analyzing stock trading data from Stuttgart Stock Exchange shows that retail investors (i. e., human investors) tend to have strong round number biases (Research Question 3c). Comparing market and limit orders reveals that the usage of limit order (prices) is the main driver of excessive buy-sell imbalances of retail investors, while market orders are almost unbiased. Furthermore, the effects on the retail investor market remain stable over time.

In sum, it is remarkable that highly sophisticated and internationalized financial markets still show imperfections induced by the behavior of market participants that are locally distinct. While the negotiation argument by Harris (1991) is sound for markets where investors directly interact or submit orders by telephone to their broker, potential impacts thereof should be less important for fully electronic markets. Another argument proposing easier calculations and better recognition is naturally still valid for today's markets and investors, but the functionality of most brokerage accounts should diminish these mental shortcomings. Many trading accounts simplify order submission to a large extend, e. g., the order value is automatically calculated for the specified price and quantity. The application of round numbers when entering limit prices needs the same effort for each limit or stop price (disregarding sub-cent price ticks). Thus, the cognitive influence of numbers and strategic considerations when making investment decisions seem to be dominant drivers.

A reason for the negative trend in round number effects might be an increasing share of algorithmic trading and higher investor sophistication. While this study presents no quantifiable arguments, the increasing share of algorithmic traders, who should be unbiased with respect to numbers, could lead to the shown decrease in round number effects. An explanation based on (human) retail investors becoming aware of their round number biases is ruled out by the results from Stuttgart Stock Exchange.

The causality between algorithmic trading and round number effects is of course limited, since the explicit strategies employed are not known. Empirical studies suggest that many algorithmic and high-frequency trader run market-making strategies and as such could strongly depend on recent order flow information (e. g., Hendershott et al., 2011). From a strategic trading perspective, market makers who identify order flow on some price level being less informed on average could considerably decrease their adverse selection risks when trading against such orders. If excessive limit order volume on round numbers signals a greater share of potentially uninformed retail investors, trading against these orders is less risky and providing liquidity on the other side of the book becomes more attractive.

The recent study by Kuo et al. (2015) confirms that clustered orders by retail investors in the Taiwanese stock market suffer considerable losses. Put differently, other market participants are able to trade successfully against these orders. This rules out the interpretation that round limit prices are an effective mechanism to signal uninformed trading intentions to the market to incentive others to trade. On the other hand, the intensity of round number effects could be used as a measure of algorithmic (institutional) trading intensity and investor sophistication.

This chapter has direct implications for the trading efforts of retail investors. As shown by BHJ, buying below and selling above round numbers results in negative (excess) returns compared to other price levels, for example. By becoming aware of their cognitive bias towards round numbers, human investors could improve the perception of current prices and also the precision of their price estimates. For example, Linnainmaa (2010) shows that the under-performance of retail investors can be explained (to some extent) by the use of limit orders. Specifically, when submitting limit orders, investors should take into account that an imprecise limit price might not serve best for their trading purpose. First, in a fast trading environment their limit orders face a large adverse selection risk which additionally increases in the presence of low-latency market participants (cf. Linnainmaa, 2010). Second, setting limit orders preferentially on or around round numbers could convey information into the market that the order is more likely to be uninformed. At the same time the execution probability decreases because of the high clustering. In both cases, retail investors presumably underestimate the amount of information and the option to trade, which they both provide to the market.

Interestingly, the New York Stock Exchange abolished stop-orders in February 2016 (New York Stock Exchange, 2015), because the exchange expects it "will help raise awareness around the potential risks during volatile trading" (Reuters, 2015). Furthermore, the NYSE states that "many retail investor use stop orders as a [...] protection"

(Pisani, 2015). In particular, the results from retail investors on Stuttgart Stock Exchange presented in this chapter indicate that the intense use of stop-orders on round numbers could be problematic. The large amounts of stop-orders on round numbers can be anticipated by other traders and identified as potentially less informed. In addition, traders might push prices to reach or penetrate round number levels in order to earn low-risk revenues for providing liquidity to the triggered stop-orders causing a short-lived directional liquidity shock that reverts afterwards.

The relation between market efficiency and round number effects remains ambiguous. In particular, it is unclear whether an (theoretical) anomaly like round number effects generally should be associated with an inefficient trading mechanism. Either way, the regulatory discussion in Europe[4] about the necessity for a slowdown of market operation and a limitation of high-frequency trading has brought up the question which tick size rule is appropriate. A suggestion has been to increase tick sizes again, since very small ticks do (presumably) not exhibit an economical benefit and have no practicable use for human investors. In relation to price clustering and buy-sell imbalances, my study can support this view in terms of round number effects as they do not considerably decrease due to smaller tick size providing evidence that smaller price increments are not adopted by human investors.

A limitation of the presented study is the unavailability of individual trading information which would allow to investigate round number biases on a subject level. Thus, an interesting extension could be to analyze brokerage account data to measure the actual impact of round number biases on the individual performance. A distinction between human and algorithmic trades (in the same market) could be promising to detect different patterns in the use of numbers for these groups. Furthermore, such data could be used to verify the impact of algorithmic trading on round number effects and test whether the degree of price clustering and buy-sell imbalances constitutes an effective indicator for trading activity of algorithmic traders and retail investors, respectively.

[4]Compare with European Securities and Markets Authority Consultation paper ESMA/2011/224, among others (https://www.esma.europa.eu/sites/default/files/library/2015/11/2011_224.pdf accessed on June 27, 2016).

Chapter 5

Conclusion and Outlook

Achieving investment and trading goals in financial markets effectively and efficiently is an arduous task for investors. Behavioral finance research identifies the impact of biased human behavior and decision making on the outcome of their investment and trading efforts. Behavioral biases are caused by the application of cognitive heuristics used to simplify the decision complexity. To overcome the complexity of the investment problem outlined in Section 1.1, investors typically use investment heuristics to find solutions to meet their goals, while cognitive and knowledge limitations are clearly driving factors for the usage.

In this thesis, I analyze the role of Technical Analysis and round number effects for retail investors trading as well as for the microstructure of stock markets. This chapter summarizes the main contributions of the presented research and discusses its implications. Furthermore, future research topics deduced from the results of the thesis are outlined.

5.1 Contributions

This thesis shows how the imperfect trading intentions influence the trading behavior of retail investors and the microstructure of stock trading on Xetra. Chapter 3 assesses the relation of Technical Analysis and retail investor trading as well as trading of large-cap stocks along two overarching research questions.

Research Question 1. *Do investment heuristics that are summarized as Technical Analysis influence retail investor trading in speculative structured products?*

Research Question 2. *What is the relation between Technical Analysis trading signals and the market quality on Xetra?*

The foundation for both research questions is the selection, calibration, and implementation of Technical Analysis techniques from which the resulted trading signals are analyzed. Therefore, I review related academic literature as well as textbooks on Technical Analysis to select 'typical' techniques and strategy calibrations. Specifically, chart patterns, moving averages, as well as support and resistance levels are considered.

The empirical analysis of Research Question 1 focuses on two types of structured products namely plain vanilla warrants and knock-out warrants on DAX and DAX30 stocks traded on Stuttgart Stock Exchange. Thus, Technical Analysis trading signals in the respective underlyings are considered. Overall, retail investor trading activity is substantially increased on days of such trading signals. A trading signal from the considered chart patterns[1] is associated with a 35 percent increase in excess turnover, on average. Moving average signals are associated with an increase of 11 percent. Furthermore, round-trip trades in accordance to Technical Analysis buy or sell signals show different characteristics than comparable trades on non-signal days. These trades exhibit a better performance, less leverage, and shorter holding duration. Using Technical Analysis signals to cluster round-trip trades into groups, those trades in accordance with Technical Analysis trading signals realize a significantly more right-skewed return distribution.

The findings on Research Question 1 contribute to the literature in several ways. First, they provide evidence that Technical Analysis is a relevant factor for retail investors trading structured products, which has been conjectured as a potential motivation to trade such products (cf. Meyer, 2014). Further, the results on realized returns of round-trip trades provide empirical support for the theoretical (simulation) results of Ebert and Hilpert (2014) arguing that payoffs from Technical Analysis strategies lead to right-skewed return distributions, which should be preferred by investors having prospect theory preferences.

[1] Specifically, Head-and-shoulder and inverse Head-and-shoulder patterns, Double Tops and Bottoms, as well as Rectangle Tops and Bottoms.

Since I also find that performance of Technical Analysis related round-trip trades is better although leverage is lower, retail investors using Technical Analysis might be more sophisticated than other retail investors trading structured products. In this sense, Technical Analysis might be a tool for retail investors to pursue strategies which help them to overcome behavioral biases such as the disposition effect.

Interpreting the relevance of Technical Analysis for retail investors as a demand for Technical Analysis tools or, more general, as a demand for a guiding system, has practical implications for the retail financial service industry. In this sense, efforts of Börse Stuttgart and other (online) information providers to make data, data visualization, and automated analysis tool available on their websites and trading accounts can be considered as a valuable service for retail investors.

On the other hand, such tools and services could misguide retail investors as the conveyed trading recommendation make people to be overconfident about what and when to trade without considering the broader view on the individual investment problem (e. g., investment goals and horizon, risk preferences, portfolio composition, and cost awareness). Obviously, there exists a conflict of interest as brokers and exchanges are interested in high turnover rates of their clients' portfolios, while academic findings identify trading costs and product costs as important drivers of the underperformance of retail investor portfolios.

The second main research question assesses the relation of Technical Analysis and the microstructure of stock trading on Xetra. Since from an academic perspective Technical Analysts are a prime example of noise traders (as they trade on past price information), the resulting effects on the trading process are of interest as classical market microstructure models (e. g., Glosten and Milgrom, 1985) predict declining implicit trading costs as a consequence of the reduced adverse selection risk of liquidity suppliers (market makers).

The study of Research Question 2 runs along three dimensions: liquidity, informational efficiency, and price discovery. These dimensions are analyzed with respect to the popular Technical Analysis techniques (simple) moving averages as well as support and resistance level. The large-scale analysis of Xetra trading of DAX30 stocks shows that limit order supply increases significantly on support and resistance levels, while after moving average signals particularly drive liquidity demand. Both results are in accordance to the findings by Kavajecz and Odders-White (2004) on the NYSE in the late 1990s. In contradiction to the latter and other related studies, Technical Analysis signals are not associated with lower implicit trading costs due to potentially reduced adverse selection risk for liquidity suppliers. However, informational efficiency measured by variance ratios, return auto-correlation, and delay is not (support and resistance levels) or only weakly (moving averages) related to Technical Analysis signals, i. e., long-term price efficiency is not harmed

Analyzing high-frequency price behavior by means of a price decomposition obtained from state space models of midquote prices, Technical Analysis trading signals turn out to have an impact on permanent and transitory price changes. Pricing errors tend to be larger in the direction of an active support or resistance level, i. e., pricing errors are significantly positive at resistance levels and negative at support levels. Moving average signals induce overpricing after a long signal and underpricing at short signals, i. e., pricing errors are in line with the recommended trade direction. However, permanent price changes rise disproportionately compared to pricing errors implying that price moves are relatively persistent after such signals. The latter is an indication for persistent liquidity demand in direction of the signal, which might be an explanation for rising or unchanged spreads around signals. Despite the higher probability to trade against uninformed Technical Analysis traders, liquidity suppliers would be faced with noise traders herding on one side of the market, making liquidity provision or arbitrage trading less attractive.

Assuming that TA signals contain no fundamental information about some stock and are not systemically related to external idiosyncratic information events, the results show that price discovery is influenced by Technical Analysis signals. The findings contribute to empirical market microstructure research by highlighting the relevance of investment heuristics such as Technical Analysis for the microstructure of stock trading. In particular, liquidity and price discovery can be significantly influenced by trading signals and thereby provides one answer to Subrahmanyam (2007) question on "whose biases affect prices" (see Section 1.1). Additionally, the empirical analysis complements theoretical evidence from models considering noise trading under limited arbitrage such as De Long et al. (1990a) and De Long et al. (1990b). In particular moving average strategies seem to be able to cause permanent price deviations as they encourage short-term (positive) feedback trading.

On the other hand, the presented research adds to the literature on Technical Analysis supporting the view of other empirical studies that moving averages plays a role for the German stock market and adds novel evidence that support and resistance levels are related to liquidity supply (i. e., limit order book volume). Since a great share of trading on Xetra is due to algorithmic traders, it seems likely that Technical Analysis related strategies play a role for some of them, i. e., Technical Analysis is not only an issue for retail investors.

The analyses of implicit trading costs imply for both techniques that pursuing such strategies does not reduce costs for demanding liquidity as a result of potentially reduced adverse selection risks for liquidity supplier, but implicit trading costs can even increase. For liquidity demander who want to trade large volume, support and resistance level could be helpful to locate high volumes of limit order supply in the book.

The third research question, which is discussed in Chapter 4, considers a long-standing stylized fact of stock trading, namely round number effects and limit order clustering.

Research Question 3. *How do round number biases influence trading on the German stock market?*

First of all, this thesis provides empirical evidence that round nubmer effects are present in the German stock market. Trading data from Xetra shows excessive buy-sell-imbalances adjacent to round numbers, but in contrast to results by Bhattacharya et al. (2012) on the NYSE the effects appear to have local characteristics. In particular, there is no quarter effect in Germany. Instead, 20-cent price levels tend to exhibit larger imbalances, which seem to be in relation to the local currency (Euro vs. Dollar coins) and historic trading conditions (eighth and sixteenth tick sizes in the U.S. market) that serve as cognitive reference points for market participants.

The study contributes to the literature by identifying drivers of buy-sell-imbalances and how they develop over time. Higher price levels are associated with larger buy-sell imbalances around round numbers. Likewise, smaller tick size lead to stronger round number effects as limit orders can be distributed over more price steps. However, the latter is superimposed by the overall negative trend in round number effects, which is stable over the sample period. This apparent trend could be related to an increasing share of algorithmic traders who are hardly effected by number biases.

The novel finding regarding this research questions is provided by the analysis of stock trading data from Stuttgart Stock Exchange as an assessment of human (retail investor) behavior. Comparing market and limit orders reveals that the usage of limit orders (prices) is the main driver of excessive buy-sell imbalances of retail investors, while market orders are almost unbiased. Furthermore, the effects on the retail investor exchange remain stable over time. This suggests that the main cause for round number biases is the implementation of limit order, i. e., the specification of limit price, and the undercutting effect is most dominant factor for buy-sell imbalances of those suggested by Bhattacharya et al. (2012).

The implications for retail investor are twofold. As Kuo et al. (2015) confirm for the Taiwanese stock market, clustered retail investor orders suffer considerable losses. Put differently, other market participants are able to trade successfully against these orders. By becoming aware of their cognitive bias regarding round numbers, human investors could improve their perception of current prices, the precision of their price estimates, and their trade implementation strategy. With respect to limit orders, they must become aware of the risk being adverse selected (cf. Linnainmaa, 2010). Second, retail investors need to realize that setting limit orders preferentially on or close to round numbers can convey information into the market signaling that the order is more likely to be uninformed, while no other positive effects are obtained in return (Kuo et al., 2015).

The results on Research Question 3 should motivate the retail financial service industry to enhance the support for their clients implementing trades, e. g., to increase the awareness of associated risk of each order type or decision support for the selection of the right order type given the purpose of a trade. Along the same line, the NYSE recently abolished stop-orders (New York Stock Exchange, 2015), because the exchange operator expects it "will help raise awareness around the potential risks during volatile trading" (Reuters, 2015). The change of trading rules indicates the NYSE suspects that retail investor do not fully understand stop-orders, which require the specification of a stop price comparable to the limit price of limit orders.

5.2 Outlook

Empirical research highly depends on the available data and information used to address the research questions of interest. This thesis has explored the meaning of Technical Analysis and round number biases on the basis of public exchange data. An analysis of other data sources that describe investor behavior on financial markets could provide further insights helping to understand investor behavior and to support them in achieving their investment goals. Similar, more detailed (stock) trading data providing further information on the identities of market participants could help to improve the understanding of the microstructure of trading. In the following, I discuss several research topics as well as potential practical implementations that could advance or build on the results and implications of the research presented in this thesis.

Market Microstructure and Noise Trading

Besides the considered Technical Analysis techniques and round number biases, there are a lot more trading styles which might cause a significant amount of noise in securities markets. With respect to Technical Analysis, a selection of specific strategies were analyzed in this thesis. Hence, there is room to explore which strategies are adopted most by market participants in order to isolate situations when noise trading is most intense. Although I have argued against the approach to 'reverse engineer' the calibration of Technical Analysis strategies by finding those parameters maximizing some objective function (e. g., turnover), this approach could provide interesting insights when combined with more precise trading information such as (anonymized) trader IDs or identifiers for specific types of market participants (e. g., algorithmic trader).

By identifying eminent signals in relation to some group of traders, we could analyze their role in specific trading environments (e. g., volatile trading). This role could be of significant importance given (automated) trading on Technical Analysis impounds additional liquidity demand in the direction of large price moves, e. g., when moving average signals are triggered in course of a price shock. Thereby we could gain additional insights regarding the role of noise trading in different market situations.

Analysis of Retail Investor Brokerage Accounts

The results presented in this thesis refer to the population of retail investors. Data on individual trading efforts from brokerage accounts could add interesting insights on the particular usage of specific trading heuristics (similar to the studies by Hoffmann and Shefrin (2014), Etheber et al. (2014), and Bhattacharya, Hackethal, Kaesler, Loos, and Meyer (2012)). However, the mere observation of account activities is not sufficient to show whether retail investors meet their investment goals, for instance, when their main intention is to gamble for entertainment reasons. Thus, complementary surveys and socio-demographic information are needed to obtain a complete view on the investor. Such complete data sets could be a promising foundations to identify aspects of the implementation of trading heuristics and provide insights where retail investors could benefit most from additional support or, in other words, where they make the most severe mistakes.

While brokerage data has been extensively studied in several dimensions, actual methods to support brokerage clients have rarely been tested from a scientific perspective and therefore have a lot of potential for future research. First interesting approaches consider unbiased investment advise (Bhattacharya, Hackethal, Kaesler, Loos, and Meyer, 2012) and personalized reports for retail investors (Meyer et al., 2015).

Empirical Assessment of Information Channels and Types on Financial Websites

Financial websites are important information sources for many investors. Typical financial websites[2] provide numerous different types of information and analyses, such as news, economic indicators, corporate fundamentals, price histories, and tools like data visualizations (charts), Technical Analysis, and order flow analysis. While there is evidence on aggregate behavior around news (Barber and Odean, 2008), stock message boards (Antweiler and Frank, 2004), TV shows (Engelberg et al., 2011), Google search volume (Da et al., 2011), and other attentions effects, the actual usage of financial websites by (retail) investors is mainly unexplored. Since modern website are able to track a lot of information on their visitors (e. g., click paths, cookie information, client

[2]See among many others, `http://www.marketwatch.com/`, `http://www.finanzen.net/`, and `https://www.boerse-stuttgart.de/`.

information) and many of these websites have contents for registered users only (e. g., watchlists), there is a lot of individual information available.

The information on individuals as well as on the usage of the website could provide interesting insights on the role of different information sources for retail investors' information processing and decision making. Furthermore, the identification of information demand with respect to individual characteristics of the user could be utilized to improve information supply for retail investors, for instance, to reduce information overload by improved information selection and preprocessing.

Experimental Analysis of Investor Behavior and Data Visualizations

Empirical studies lack the possibility to isolate single effects and biases in decision making for several reasons. Foremost, the unavailability of personal information on the individuals and the impact of superimposing effects as a consequence of an uncontrolled environment and setting limit the explanatory power. Laboratory experiments can be used to partly overcome such problems and allow the assessment of very specific effects.

In the context of this thesis, an interesting question is how trading heuristics influence the decision making process on an individual level. More specifically, Technical Analysis tools and data visualization could be considered. Existing experimental studies analyze how price charts and visualizations alter the belief in trends and their strength with respect to forecasts and the confidence about future price developments (e. g., Mussweiler and Schneller, 2003; Glaser et al., 2007; Rötheli, 2011). Mostly unexplored in these studies is how the actual trading behavior is influenced, i. e., do participants trade more frequently and is their risk taking behavior and risk perception influenced by trading heuristics such as Technical Analysis. Experimental evidence by Kaufmann et al. (2013) shows that risk perception can be positively supported by graphical displays and experience sampling of risk. While the latter implies a positive effect of visualizations (information presentation), the fact that the behavior is influenced at all suggests that a manipulation of behavior in a manner which is not beneficial for the investors is possible, too.

In sum, experimental research as described above could serve as a foundation for future initiatives to build systems and tools that support (retail) investors in making financial decisions. Furthermore, it could provide insights on the effects of the increased application of data visualizations and chart tools in brokerage accounts. If it turns out that these tools encourage users to act in contrast to their actual intentions and preferences, this line of research could provide arguments whether such offerings are appropriate for certain investors, e. g., financially illiterate investors.

Decision Support for Retail Investors and Financial Education

Section 1.1 motivated the presented research on the basis of a stylized investment process. As discussed, there is evidence that households' investment performance is suboptimal, but the reasons therefore are manifold. The question arises how retail investors can be supported to meet their investment goals, e. g., a solid retirement provision.

In recent years, the start-up industry in the financial service sector is rapidly growing. Several so-called Fintechs have developed automated online asset management accounts, which intend to compete with classical (online) brokerage and banking services. Their key selling point is simple and automated investment advise coming at relatively low costs compared to classical bank advisers or wealth managers. The automated advisory (so-called robo-advisory) typically seeks to capture the clients' financial situation and goals from which default solutions are derived and offered to the client. In that respect, the scope and complexity of robo-advisors is fairly limited and current features are far from fully digitalizing real investment advisers. For instance, it seems questionable whether the average retail investor is able to formulate a suiting investment goal given her financial situation because the relevance of different dimensions can be fairly complex (e. g., forecasts of income and consumption rates).

Hence, there is much room to enhance the support of (retail) investors with regard to the stylized investment process. First of all, since the average level of financial literacy in Germany (and other countries alike) is considered as low, additional financial education offers are required, e. g., in schools or on online (learning) platforms. However, it is unclear how to support self-directed financial decision making in an effective way, i. e., which parts of the investment problem should be supported and which can be automated. The meta-analysis by Fernandes et al. (2014) suggests that financial education decays over time and, thus, ad-hoc decision support might be more valuable than single education programs. How ad-hoc decision support in a retail investment context can be realized in an effective way is an open question for future research that would provide an extensive social benefit.

Appendix A

Supplementary Materials

A.1 Supplementary Materials for Chapter 2

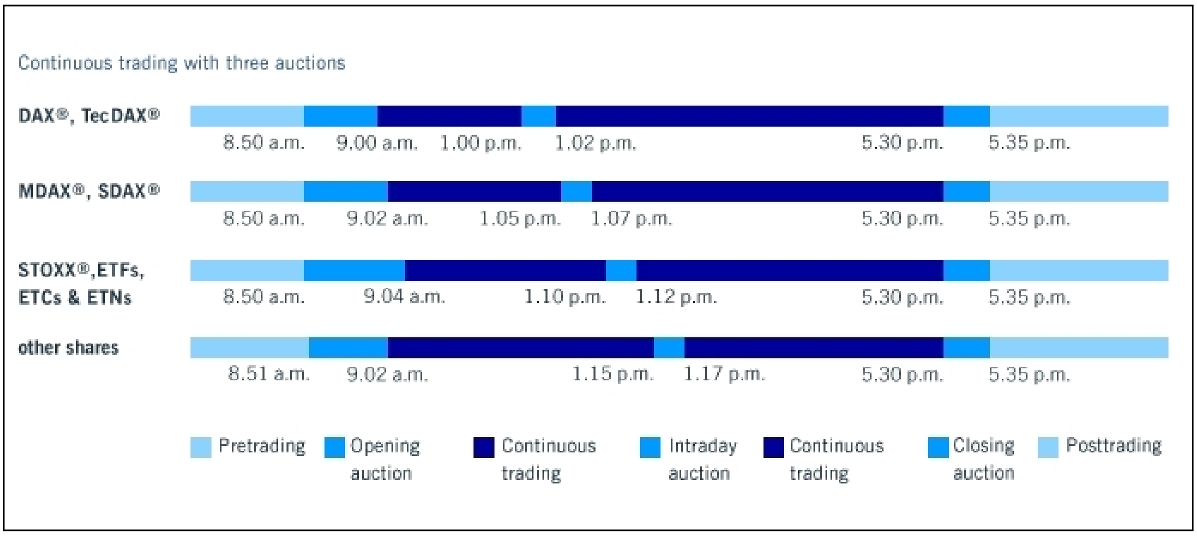

FIGURE A.1: **Xetra Trading Schedule.** This figure shows the official continuous trading and auction schedule of Xetra for different types of securities. Source: Deutsche Börse, `http://www.xetra.com/xetra-en/trading/trading-information/auction-schedule` (accessed on August 9, 2016).

TABLE A.1: **Thomson Reuters Tick History – Times & Sales Data Example.** This table shows a few seconds of Xetra trading in the stock of RWE AG. Quote observations only show changes in the prevailing quote. Trade observation report trade price and volume of an executed trade. Qualifiers denote message flags which provide coded message details.

RIC	Date[G]	Time[G]	GMT Offset	Type	Price	Volume	Bid Price	Bid Size	Ask Price	Ask Size	Qualifiers
RWEG.DE	24.Jan12	08:29:02.308	1	Quote			26.385	295		345	TRADE [GV1_TEXT]; [PRC_QL2]
RWEG.DE	24.Jan12	08:29:02.791	1	Trade	26.4	345					TRADE [GV1_TEXT]; [PRC_QL2]
RWEG.DE	24.Jan12	08:29:02.809	1	Quote			26.395	125	26.415	77	TRADE [GV1_TEXT]; [PRC_QL2]
RWEG.DE	24.Jan12	08:29:02.880	1	Trade	26.405	125					TRADE [GV1_TEXT]; [PRC_QL2]
RWEG.DE	24.Jan12	08:29:03.312	1	Quote				995			TRADE [GV1_TEXT]; [PRC_QL2]
RWEG.DE	24.Jan12	08:29:03.811	1	Quote				1606	26.42	378	TRADE [GV1_TEXT]; [PRC_QL2]
RWEG.DE	24.Jan12	08:29:04.326	1	Quote			26.405	295	26.425	714	TRADE [GV1_TEXT]; [PRC_QL2]
RWEG.DE	24.Jan12	08:29:04.817	1	Quote				602	26.415	340	TRADE [GV1_TEXT]; [PRC_QL2]
RWEG.DE	24.Jan12	08:29:05.305	1	Quote				1141			TRADE [GV1_TEXT]; [PRC_QL2]
RWEG.DE	24.Jan12	08:29:05.526	1	Trade	26.41	17					TRADE [GV1_TEXT]; [PRC_QL2]
RWEG.DE	24.Jan12	08:29:05.573	1	Trade	26.41	295					TRADE [GV1_TEXT]; [PRC_QL2]
RWEG.DE	24.Jan12	08:29:05.837	1	Quote				602	26.41	119	TRADE [GV1_TEXT]; [PRC_QL2]
RWEG.DE	24.Jan12	08:29:07.934	1	Quote				307			TRADE [GV1_TEXT]; [PRC_QL2]

TABLE A.2: **Sample of DAX30 Stocks.** The table lists the 30 DAX stocks analyzed in this thesis. Stock names are obtained from Deutsche Börse Cash Market Statistics (`http://goo.gl/N5pagN` accessed on August 9, 2016.). Stock names are stated with the following German abbreviations (English translation in parentheses). "NA" Namensaktie (registered share); "VNA" vinkulierte Namensaktie (registered share with restricted transferability); "O.N." Ohne Nennwert (no-par-value); "VZO" Vorzugsaktie ohne Stimmrecht (non-voting bearer preferred share).

Stock Name	RIC	ISIN
ADIDAS AG NA O.N.	ADSGn.DE	DE000A1EWWW0
ALLIANZ SE VNA O.N.	ALVG.DE	DE0008404005
BASF SE NA O.N.	BASFn.DE	DE000BASF111
BAYER AG NA	BAYGn.DE	DE000BAY0017
BEIERSDORF AG O.N.	BEIG.DE	DE0005200000
BAYRISCHE MOTOREN WERKE AG ST	BMWG.DE	DE0005190003
COMMERZBANK AG	CBKG.DE	DE000CBK1001
CONTINENTAL AG O.N.	CONG.DE	DE0005439004
DAIMLER AG NA O.N.	DAIGn.DE	DE0007100000
DEUTSCHE BANK AG NA O.N.	DB1Gn.DE	DE0005140008
DEUTSCHE BOERSE NA O.N.	DBKGn.DE	DE0005810055
DEUTSCHE POST AG NA O.N.	DPWGn.DE	DE0005552004
DEUTSCHE TELEKOM AG NA	DTEGn.DE	DE0005557508
E.ON SE NA	EONGn.DE	DE000ENAG999
FRESENIUS MEDICAL CARE KGAA O.N.	FMEG.DE	DE0005785802
FRESENIUS SE+CO.KGAA O.N.	FREG.DE	DE0005785604
HEIDELBERGCEMENT AG O.N.	HEIG.DE	DE0006047004
HENKEL AG+CO.KGAA VZO	HNKG_p.DE	DE0006048432
INFINEON TECHNOLOGIES AG NA O.N.	IFXGn.DE	DE0006231004
K+S AG NA O.N.	LHAG.DE	DE000KSAG888
LANXESS AG	LING.DE	DE0005470405
LINDE AG O.N.	LXSG.DE	DE0006483001
LUFTHANSA AG VNA O.N.	MRCG.DE	DE0008232125
MERCK KGAA O.N.	MUVGn.DE	DE0006599905
MUENCHER RUECKVERSICHERUNG VNA O.N.	RWEG.DE	DE0008430026
RWE AG ST O.N.	SAPG.DE	DE0007037129
SAP AG O.N.	SDFGn.DE	DE0007164600
SIEMENS AG NA	SIEGn.DE	DE0007236101
THYSSENKRUPP AG O.N.	TKAG.DE	DE0007500001
VOLKSWAGEN AG VZO O.N.	VOWG_p.DE	DE0007664039

TABLE A.3: **Sample of MDAX50 Stocks.** The table lists the 50 MDAX stocks analyzed in this thesis. Stock names are obtained from Deutsche Börse Cash Market Statistics (`http://goo.gl/N5pagN` accessed on August 9, 2016.). Stock names are stated with the following German abbreviations (English translation in parentheses). "NA" Namensaktie (registered share); "VNA" vinkulierte Namensaktie (registered share with restricted transferability); "O.N." Ohne Nennwert (no-par-value); "VZO" Vorzugsaktie ohne Stimmrecht (non-voting bearer preferred share).

Stock Name	RIC	ISIN
A.SPRINGER SE VNA	SPRGn.DE	DE0005501357
AAREAL BANK AG	ARLG.DE	DE0005408116
AIRBUS GRP (LEGALLY EADS)	EADS.DE	NL0000235190
BAYWA AG	BYWGnx.DE	DE0005194062
BILFINGER SE O.N.	GBFG.DE	DE0005909006
BRENNTAG AG	BNRGn.DE	DE000A1DAHH0
CELESIO AG NAM. O.N.	CLSGn.DE	DE000CLS1001
DEUTSCHE EUROSHOP AG O.N.	DEQGn.DE	DE0007480204
DEUTSCHE WOHNEN AG INH	DWNG.DE	DE000A0HN5C6
DMG MORI SEIKI AG O.N.	GILG.DE	DE0005878003
DOUGLAS AG	DOHG.DE	DE0006099005
DUERR AG O.N.	DUEG.DE	DE0005565204
ELRINGKLINGER AG NA O.N.	ZILGn.DE	DE0007856023
FIELMANN AG O.N.	FIEG.DE	DE0005772206
FRAPORT AG FFM.AIRPORT	FRAG.DE	DE0005773303
FUCHS PETROL.SE VZO O.N.	FPEG_p.DE	DE0005790430
GAGFAH S.A. NOM. EO 1,25	GFJG.DE	LU0269583422
GEA GROUP AG	G1AG.DE	DE0006602006
GERRESHEIMER AG	GXIG.DE	DE000A0LD6E6
GERRY WEBER INTERNATIONAL O.N.	GWIG.DE	DE0003304101
GSW IMMOBILIEN AG	GIBG.DE	DE000GSW1111
HAMBURGER HAFEN UND LOGISTIK AG	HHFGn.DE	DE000A0S8488
HANN.RUECK SE NA O.N.	HNRGn.DE	DE0008402215
HOCHTIEF AG	HOTG.DE	DE0006070006
HUGO BOSS AG NA O.N.	BOSSn.DE	DE000A1PHFF7
KABEL DT. HOLDING AG O.N.	KD8Gn.DE	DE000KD88880
KLOECKNER + CO SE NA	KCOGn.DE	DE000KC01000
KRONES AG O.N.	KRNG.DE	DE0006335003
KUKA AG	KU2G.DE	DE0006204407
LEONI AG NA O.N.	LEOGn.DE	DE0005408884
MAN SE ST O.N.	MANG.DE	DE0005937007
METRO AG ST O.N.	MEOG.DE	DE0007257503
MTU AERO ENGINES NA O.N.	MTXGn.DE	DE000A0D9PT0
NORMA GROUP SE NA O.N.	NAFG.DE	DE000A1H8BV3

Continued on next page

Continued from last page

PROSIEBENSAT.1 NA O.N.	PSMG_p.DE	DE000PSM7770
PUMA SE	PUMG.DE	DE0006969603
RATIONAL AG	RAAG.DE	DE0007010803
RHEINMETALL AG	RHMG.DE	DE0007030009
RHOEN-KLINIKUM O.N.	RHKG.DE	DE0007042301
SALZGITTER AG O.N.	SZGG.DE	DE0006202005
SGL CARBON SE O.N.	SGCG.DE	DE0007235301
SKY DTLD AG NA	SKYDn.DE	DE000SKYD000
STADA ARZNEIMITTEL VNA O.N.	STAGn.DE	DE0007251803
SUEDZUCKER MA. O.N.	SZUG.DE	DE0007297004
SYMRISE AG INH. O.N.	SY1G.DE	DE000SYM9999
TAG IMMOBILIEN AG	TEGG.DE	DE0008303504
TUI AG NA	TUIGn.DE	DE000TUAG000
VOSSLOH AG	VOSG.DE	DE0007667107
WACKER CHEMIE O.N.	WCHG.DE	DE000WCH8881
WINCOR NIXDORF O.N.	WING.DE	DE000A0CAYB2

A.2 Supplementary Materials for Chapter 4

TABLE A.4: **Tobit Regression Model of Buy-sell Imbalances in DAX and MDAX.** The table shows regression results estimated from the pooled data of DAX and MDAX stocks. The dependent variable is the absolute order imbalance. The sample period spans from January 2009 to December 2013. The regression equation is defined as $|Imba| = \sum_{i=1}^{5} \beta_i * centdummy_i + \sum_{i=1}^{5} \gamma_i * centdummy_i * MDAX + \delta * AvgPrice + \sum FixedEffects$, where $FixedEffects$ denote stock and year dummies. *, **, and *** denote significance on the 10%, 5%, and 1% level.

	Order Imbalance	
	Estimate	Std. Dev.
Integer (.99, .01)	0.1693***	0.0068
Integer * MDAX	0.0718***	0.0087
Half-Euro (.49, .51)	0.1243***	0.0068
Half-Euro * MDAX	0.0638***	0.0087
20-Cents (.19, .39, .59, .79, .19, .39, .59, .79)	0.0715***	0.0036
20-Cents * MDAX	0.0213***	0.0046
10-Cents (.09, .29, .69, .89 .11, .31, .71, .91)	0.0625***	0.0036
10-Cents * MDAX	0.0235***	0.0046
5-Cents (.04, .14, .24, .34, .44, .54, .64, .74, .85, .94, .06, .16, .26, .36, .46, .56, .66, .76, .86, .96)	0.0152***	0.0025
5-Cents * MDAX	-0.0026	0.0031
Average Price	0.0638**	0.0087

TABLE A.5: **The Impact of Tick Size Regimes on Conditional Buy-Sell Imbalances – Subsample Analysis.** The logistic regression model shown in this model is equivalent to the model reported in Tabel 4.6 but estimated on a subsample of the original analysis including Q4/2009 and Q1/2010 only. The regression model is specified as $OrderImba = \alpha + \sum_{i=1}^{6}(\beta_i^{(1)} * int_i + \beta_i^{(2)} * int_i * dummy2010 + \beta_i^{(3)} * int_i * tick + \beta_i^{(4)} * int_i * tick * dummy2010 + \sum_{j=1}^{4} \gamma_i^{(j)} fiveC_i * [...]) + \sum controls.$ Controls include fixed effects for stock and year as well as dummies for penny-endings (0 to 9), turnover, volume, and the trade direction of the previous trade. The table shows differences in coefficient estimates between the integer and 5-cent group with respect to the tick size dummy and the dummy for trades in 2010, as well as their intersection. Column 'No Dummy' shows the baseline effect, i.e. stocks traded between EUR 50 and EUR 100 in 2009. Columns 'Dummy 2010' and 'Tick Size Dummy' measure overall changes in 2010 and the difference of effects in the group of trades between EUR 2 and EUR 50. The column 'Tick Size & 2010' shows the differences in the interaction term which measure the impact of the new tick size regime. P-values for coefficient differences are obtained from Wald tests.

	No Dummy $\beta_i^{(1)} - \gamma_i^{(1)}$		Dummy 2010 $\beta_i^{(2)} - \gamma_i^{(2)}$		Tick Size Dummy $\beta_i^{(3)} - \gamma_i^{(3)}$		Tick Size & 2010 $\beta_i^{(4)} - \gamma_i^{(4)}$	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
Ask falls below integer- Ask falls below nickel	0.0502	<0.0001	-0.0219	0.0248	-0.0283	0.0004	0.0242	0.0012
Ask rises while staying below integer- Ask rises while staying below nickel	0.0801	<0.0001	-0.0209	0.0261	-0.0468	0.0011	0.0368	0.0437
Ask falls to integer- Ask falls to nickel	0.3702	<0.0001	-0.0508	0.0525	-0.0549	0.0266	0.0645	0.0655
Bid rises to integer- Bid rises to nickel	-0.4114	<0.0001	0.0863	0.0012	0.1392	<0.0001	-0.1225	0.0006
Bid rises above integer- Bid rises above nickel	-0.0275	<0.0001	0.0012	0.9103	0.0237	0.0072	0.0248	0.0415
Bid falls while staying above integer- Bid falls while staying above nickel	-0.046	<0.0001	-0.0282	0.0025	0.0120	0.1515	0.0251	0.0299

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List of Abbreviations

List of Figures

List of Tables