Technical Analysis, Liquidity, and Price Discovery[*]

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Abstract

Academic literature suggests that Technical Analysis (TA) plays a role in the decision making process of some investors. If TA traders act as uninformed noise traders and generate a relevant amount of trading volume, market quality could be affected. We analyze moving average (MA) trading signals as well as support and resistance levels with respect to market quality and price efficiency. For German large-cap stocks we find excess liquidity demand around MA signals and high limit order supply on support and resistance levels. Depending on signal type, spreads increase or remain unaffected which contradicts the mitigating effect of uninformed TA trading on adverse selection risks. The analysis of transitory and permanent price components demonstrates increasing pricing errors around TA signals, while for MA permanent price changes tend to increase of a larger magnitude. This suggests that liquidity demand in direction of the signal leads to persistent price deviations.

JEL Classification: G12, G14

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1 Introduction

Technical Analysis (TA) compromises a large variety of trading strategies and methodologies which commonly share the usage of past market data of price and volume to generate trading recommendations. Technical analysts use these method to generate information about future price developments. Hence a profitability stands in direct contradiction to the efficient market hypothesis. There is strong evidence that many popular TA strategies earn no excess returns (Park and Irwin, 2007; Bajgrowicz and Scaillet, 2012), yet profitability is not our focus. Despite the lack of profitability both retail and professional investors do use TA for their investment decisions as several empirical studies show (Menkhoff, 2010; Hoffmann and Shefrin, 2014; Etheber, 2014).

The fact that some market participants adopt TA for their trading leads to the question whether TA is a self-fulfilling prophecy. If some TA signal[1] suggests rising prices and a sufficiently large number of people trade on this signal, prices will eventually rise due to excess demand. On the other hand, if there are such profitable public trading signals, one could easily trade ahead of an anticipated signal. Ultimately, the signals validity might be questioned as other traders already traded in front of it, or the TA signal would even never appear. In this scenario the strategy is self-destructive[2]. Compared to the extreme cases of of immediate self-destruction and self-fulling, a more practicable approach could involve market participants who identify price moves which do not reflect price-relevant information, for example caused by uninformed TA trades, and trade in the opposite direction which enforces efficient prices. In this case, TA has an influence on trading with respect to liquidity supply and demand and on price efficiency (noise), i.e. prices temporarily deviate from efficient levels due to uninformed TA (noise) traders. These deviations could also 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 our study.

More specifically, we assess whether trading signals derived from popular TA strategies are related to various dimensions of market quality. Our two main research questions are as follows.

> **RQ1:** *What is the effect on dimensions of liquidity supply and demand around popular TA trading signals?*

[1]We use the term TA signal for any type of signal considered in this paper, i.e. active support and resistance levels, and moving average long and short signals.

[2]Timmermann and Granger (2004) discuss the persistence of forecasting methods (e.g. technical trading) and their self-destruction characteristic.

RQ2: *Given that technical traders are uninformed noise traders, what is the effect on transitory and permanent price components when TA signals appear?*

To answer these questions we analyze trade and quote data of German large-cap stocks (DAX30) from Xetra. We use a high observation frequency to reveal short-lived effects appearing around TA signals which might not be visible or directly attributable on a high level of aggregation (e.g. daily).

Two popular TA methodologies are considered in this paper: moving averages (MA) and support and resistance levels (SRL). These methods are used to identify trends and trend reversals which are fundamental properties of stock prices in the view of technical analysts[3]. MA strategies are easily accessible and provide investors straightforward recommendations. MA signals usually suggest to trade in the direction of previous price changes and shall indicate an ongoing trend. SRL mark prices (or price ranges) where a change of direction appeared in the price path. Technical analysts interpret this occurrence as evidence that supply and demand will tend to behave similarly when prices approach the SRL once more. Furthermore, SRL play an important role in the analysis of chart patterns (e.g. double bottom, head-and-shoulder patterns) which typically involve a specific sequence of highs and lows (peaks and troughs). We identify SRL by applying a recognition algorithm based on smoothing splines.

Our main results are as follows. First, we analyze the relation of TA signals to liquidity measures. We find that the limit order book (LOB) is much deeper on levels of active SRL. When MA long (short) signals are active in an 1-minute interval turnover (liquidity demand) increases by about 15% (18%), on average, whereas it decreases in case of active SRL. Furthermore quoted spreads are about 0.48 bps to 0.62 bps higher depending on TA signals type. Second, we analyze TA signals in the context of informational efficiency by means of measures based on return auto-correlations, variance ratios, and price delay to market-wide information. For SRL we find no significant effect on these measures which implies that the associated effects on liquidity do not harm (nor improve) informational efficiency. In contrast, MA signals are related to rising inefficiency, but only in case of price delay the effect seems to be of notable magnitude[4]. Third, we apply the state space methodology introduced by Menkveld et al. (2007) to obtain a decomposition of observed prices into an efficient price component and pricing errors (transitory component). Our analysis shows that pricing errors increase significantly in direction of MA signals and the direction of active support or resistance levels, respectively. Particularly, in case of MA long (short) signals is of meaningful size. MA long (short) signals are related to

[3]See Edward and Magee (2001), Chapter 1, for example,.

[4]The daily average number of simple moving average (SMA) signals is associated with an delay measure increase of 5.8% standard deviations.

pricing errors of 0.89 bps (-0.95 bps) which is equivalent to approximately one price tick, on average. Ratios of transitory errors to total (absolute) price innovation indicate that in case of MA signals the increase in the permanent price component is larger (relative to the transitory component), while for SRL the share of transitory components is more dominant. This suggests that MA signals coincide with periods of generally increased fluctuations in both price components.

We interpret this result as evidence for persistent liquidity demand in direction of MA signals causing prices to deviate long enough from previous levels to be considered as permanent by the model. An explanation might be based on arguments derived from noise trader models by De Long et al. (1990a) and Shleifer and Vishny (1997). If we assume TA (MA) traders act in the same direction and enter the market unpredictably but clustered over a short period of time[5], the risk of adverse price movements surges for arbitrageurs. As a result, they are discouraged to trade against the pricing error. The latter could also explain the observed increase in quoted spreads if liquidity providers (market maker) try to compensate potential adverse price moves. Eventually, price impacts of trades in direction of MA signals indicate that prices actually move against liquidity demander after a while.

This paper contributes to the existing literature on TA by confirming that previous results regarding SRL and MA strategies also hold for the German stock market and on an intraday level. Furthermore we show how TA signals are related to implicit trading costs (spreads). The analysis of price efficiency around TA signals provides evidence that stock prices are influenced by trading heuristics. Thus limited rationality of some investors is not only a relevant factor for their personal performance but also for the microstructure of trading.

The remainder of the paper is organized as follows. In the following section we provide an overview of related literature and define research hypotheses. Section 3 describes the employed data sets and presents descriptive statistics. Section 4 introduces the methodological approach regarding the TA signal recognition. Results on limit order book liquidity are presented in Section 5. Section 6 considers informational efficiency of prices. In Section 7 we analyze the price decomposition into permanent and transitory components by means of State Space Models (SSM). Section 8 provides several robustness checks. Section 9 concludes.

[5]For example because TA trader use slightly different signal definitions or their time to process signals varies.

2 Related Literature and Research Hypotheses

Academic research on TA and related strategies has a long history dating back to the early sixties when, among others, Alexander (1961) examined filter rules to provide evidence that price processes deviate from random walks. Many studies focus on the profitability of various TA-related trading strategies, like filter rules, relative strength, or MA. Park and Irwin (2007) provide a literature review on the profitability and conclude that evidence regarding profitability is mixed depending on strategy and time period, but highlight potential biases. More recent papers show that some studies face data snooping biases implying that the considered TA strategies are not persistently profitable (e.g. Sullivan et al., 1999; Bajgrowicz and Scaillet, 2012). For our study the actual (long-term) profitability of some TA strategies is only of subordinate interest as we focus on liquidity and price efficiency.

Behavioristically motivated studies analyze the actual usage of TA by investors and the impact on their trading behavior. In particular retail investors seem to be interested in TA. Hoffmann and Shefrin (2014) show that retail investors who use TA perform significantly worse than the rest of the sample population. TA traders typically trade more often and take higher risk. Interestingly, the survey of Hoffmann and Shefrin (2014) shows a slight increase in the share of retail investors using TA compared to the survey by Lease et al. (1974). Easy access to information technology and data required for TA might amplify its usage by retail investors. In fact Benamar (2013) shows that a trading software upgrade, which provides more visualization features and data sources, can actually alter the trading behavior of its users. Etheber et al. (2014) find intense TA-related trading activities among German retail investors. For about 10% of the retail investors in their brokerage dataset trading activities can be consistently related to MA trading heuristics. Overall trading activity of the sample population increases 30% on MA signal days while earning no abnormal returns. Surveys among fund managers (Menkhoff, 2010) and FX traders (Cheung et al., 2004) show that TA is not only used by retail investors, but also plays a role for investment decisions of professional investors. Similarly, Wang et al. (2012) demonstrate increased institutional trading activity around signals of so-called stochastic oscillators (KD rule) in Taiwanese stocks. Thus, the overall volume of TA-related trading could actually be of relevant size.

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 TA might have a value for investors who are not fully informed. Besides, the popularity of TA 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 TA in financial media[6] from which investors could obtain similar trading signals if they use similar TA strategies.

Following the literature, we assume that TA 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). 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. Based on experiments Bloomfield et al. (2009) show that beside having positive effects on liquidity, noise trading can slow down 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 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 mispricing is persistent. Obviously, persistent mispricing would mean a substantial impairment of market quality.

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[7] and rational speculators expect their demand resulting in higher levels of price volatility than fundamentals would justify.

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 measures

[6] The actual relevance of TA in financial media and for information provider compared to other forms of information and security analysis tools (e.g. fundamental data, analysts forcasts, etc.) obviously is hard to measure and mostly subjective. Several authors argue that TA has a broad media coverage, see Park and Irwin (2007), Hoffmann and Shefrin (2014), Avramov et al. (2015).

[7] 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.

and empirical analysis of market quality trends. Many studies[8] 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, we analyze market quality in a static way, i.e. for the most part we consider 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 MA 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 MA type and signal direction). The mentioned studies on TA and market liquidity use relatively low measurement frequencies or use relative short sample periods[9]. Especially MA 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 TA and liquidity. Thus, we focus on contemporaneous effects between TA-related signals and measures of market quality.

Based on the implications of previous studies summarized above, we derive hypotheses regrading our research questions RQ1 and RQ2. Due to their relevance for the central concepts of TA and due to related academic literature, we focus on SRL and (simple) MA indicators which are defined in Section 4. Since these indicators basically lead to different

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

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

trading recommendations (MA trend following, SRL reversal), the hypothesis can differ for each type. Regarding RQ1 we establish the following hypothesis regarding liquidity demand and supply.

Hypothesis H1a: *MA trading signals can be associated with an immediate increase in trading activity.*

Hypothesis H1b: *SRL coincide with levels of excess depth in the LOB.*

Hypothesis H1c: *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, we 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.

Hypothesis H2a: *Measures of informational inefficiency rise in the presence of MA signals, i. e. price process characteristics deviate from random walk properties more intensely.*

In the context of this study, we suspect that TA signals are short-lived, so potential effects on price efficiency should be temporary as well. Therefore we 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 H2b: *Price discovery is distorted around TA signals since they are related to larger transitory pricing errors while permanent price components are not affected.*

3 Data Preparation and Descriptive Statistics

The study focuses on the thirty largest German stocks based on the DAX30 index composition at the end of 2013. For each stock we retrieve two datasets from the Thomson Reuters Tick History through SIRCA[10]. Times and Sales data contains trades and quotes on a tick-by-tick basis and orderbook depth data comprises tick-by-tick data of the first ten levels of the bid and ask side of the limit order book. We delete all observations related to opening, closing, and intraday call auctions since we are primarily interested in continuous trading. Furthermore, we perform typical data cleanings such as removing of observations with missing values. We also remove trading days when stocks have a significant amount of missing data, for example, at the beginning of the trading day. A list of stocks and the performed data cleanings can be found in the appendix. The sample period spans from January 2008 to November 2013. The first month is used to initialize the TA signal recognition but is not considered for the statistical analyses.

If trade and quote observations appear in the same millisecond, we compare trade price and size with the respective quote and quote change and sort these observations accordingly. We then use the Lee and Ready (1991) algorithm to infer the trade direction of each trade which is used for the calculation of several liquidity measures. The latter covers the common scope of trade and quote based liquidity proxies, i. e. quoted spread, effective spread, realized spread (15 min), and price impact (15min).

Based on the order book data we 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 levels six to ten and the cumulative depth on levels one to five, i. e. $\frac{Depth10-Depth5}{Depth5}$. $Depth5(Depth10)Imbalance$ 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 order book level (i. e. its limit price) with the most shares available on the ask (bid) side and the midquote price. Lastly, we calculate relative depth for each level on the 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, we 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 $[t, t+1)$, and in case of atomistic variables (e.g.

[10]We thank the Secruties Industry Research Center of Asia-Pacific (SIRCA) for providing access to the data.

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 events. 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 helps to mitigate the fuzziness arising from the potentially inexact observation of TA events (e.g. due to different calibration methods or processing times) but still is sufficiently granular to remain a high precision in the measured variables. In fact, it is an important feature of our analysis to conduct the study on an intraday level compared to existing literature on liquidity and TA which has mainly considered lower frequencies. Thereby we 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. $Range_{i,t}$ 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 $(t-1, t]$.

Insert Table 1 here.

Except for the recognition algorithm of SRL and determination of MA trading signals described in section 4, we drop the first and last 15 minutes of each trading day to avoid potential effects on liquidity measures as it is standard in the literature. Table 1 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). This is a known result on Xetra (Riordan and Storkenmaier, 2012) which is to mostly due to order types which provide hidden liquidity and features of Xetra such as Xetra Midpoint and Xetra BEST [11]. These features cause the appearance of order executions inside the spread. Since this are normal functions of continuous stock trading on Xetra, excluding the respective trades seems inconvenient with respect to measures of trading activity, liquidity, and price discovery. In December 2013, special trades originating from Xetra BEST and Xetra Midpoint account for less than 1% of trades which seems to be sufficiently small to rule out potential systematic effects on the results.

Nevertheless, we can not rule out the possibility that extremely short-lived quote

[11]Details on the Xetra trading model are listed in the official Xetra Market Model Equities documentation. `http://www.xetra.com/blob/2449728/9c92a1e153f7db3edb6ad230295dcffc/data/market-model-equities.pdf` (accessed on May 13, 2016).

observations are not reported by Xetra[12] which could cause an overestimation of quoted spreads.

4 Methodology

To analyze fluctuations in liquidity in relation to TA, we need to define the type of TA signals under consideration and the method to identify these signals. In this study we focus on MA and SRL.

In general, the implementation of MA trading strategies is relatively simple. However the selection of a specific type of MA, e.g. simple or exponentially smoothed, its duration, i. e. the number of observations of which the average is calculated, and the trigger condition[13] of the signal allow for an unlimited number of strategies and related trading signals. Since we have no information on the calibrations Technical Analysts primarily use for intraday trading, we try to keep it as unambiguous as possible and use the most standard MA, i. e. simple moving averages (SMA) 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. Thus the conditions for a long signal are $MA^d_{t-1} > p_{t-1} + ticksize$ and $MA^d_t < p_t + ticksize$. The conditions for a short signal are defined analogously. We define the indicator variables *SMA long* which equals 1 if any of the four SMA triggers a buy signal and *SMA short* which equals 1 if any of the four MA triggers a sell signal.

Technical analysts define SRL as 'significant' (local) lows and highs in the price path (Kirkpatrick II and Dahlquist, 2012, p.230f). In order to detect such levels, we use an adopted version of the approach by Lo et al. (2000), which has been used in other studies (e.g. Savin et al., 2006) in similar ways. We determine SRL for each one minute observation using a window of 510 (most recent) observations. In each window we fit a cubic spline[14]. 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. Thereby we obtain a reasonable number of SRL in calm as well as in stressed market situations. Let $vola$ denote the hourly midquote return volatility in the respective window. The recognition algorithm works as follows:

[12] To the best of our knowledge, neither SIRCA nor Thomson Reuters Tick History conflate data in their databases. Yet it seems conceivable that Deutsche Brse only reports a reasonable amount of quote and LOB information to meet their reporting obligations.

[13] For example filter bands or the crossover of two MA of different length are often used in practice.

[14] In contrast to Lo et al. (2000), who use Kernel regressions to smooth their daily price series, we use cubic splines because the calculation is more efficient. Since we use intraday data and the algorithm runs over rolling windows for each observation this improves the run time drastically.

1. Fit a cubic spline using the annualized midquote return volatility in basis points 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 (minutes) of the window.

As a result we obtain a list of active highs and lows which are relevant for the last observation within the window (i. e. the current observation). Then the window is moved by one observation and the algorithm is applied again to obtain a new list of highs and lows. Figure 1 illustrates the algorithm procedure. In the depicted 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 and in case of the minimum the current (last) midquote price is lower than the detected local minimum. Overall we obtain a list of three active maxima and one active minimum for the current price (last price in the window).

Insert Figure 1 here.

The existence of active highs and lows does not mean that a support or resistance level is necessarily active. Based on the determined extrema we define indicator variables which signal that an SRL becomes active for the current quote. The variable *AtSupport* equals 1 if 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 TA trader if she uses candlestick charts. Analogously, we define the dummy variable *AtResistance* with respect to local highs and ask quotes.

Additionally we define the variables *SupActiveL1-L5* and *ResActiveL1-L5* which signal an active support or resistance level on the first five levels of the LOB. *SupActive L6-L10* and *ResActiveL6-L10* refer to an active support or resistance level on LOB levels 6 to 10.

Insert Table 2 here.

Table 2 shows descriptive statistics for the defined variables, i.e. the number of SMA signals and SRL found. Across all stocks the relative appearance of SRL in our 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 levels (level 5 to 10) of the LOB on the bid or ask side is larger.

In comparison, MA events trigger more rarely. We find long and short events in only about 0.5% of the 1-minute intervals across the sample. Yet this seems to be a sufficiently large number to compare differences in measures in relation to the defined indicator variables given the large sample size.

5 Limit Order Book Liquidity

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

$$LM_{i,t} = \beta_1 AtSupport_{i,t} + \beta_2 AtResistance_{i,t} + \sum_j TradeVar_j + \sum FE, \qquad (1)$$

where $LM_{i,t}$ denotes the respective liquidity measures of stock i at time t, $AtSupport_{i,t}$ and $AtResistance_{i,t}$ indicate active support and resistance as specified in section 4, and $TradeVar_j$ summarize a number of trading related control variables. This includes turnover, market capitalization, (squared) midquote log-return, *Range*, VDAX[15], and the LOB measures *Depth*1, *Depth*5*Ask*, and *Depth*5*Bid*. 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[16]. We 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[17]. Section 8 presents two alternative

[15]We use the volatility index VDAXnew, which is based on the implied volatility of DAX options, as a proxy of market volatility.

[16]For example, markets mostly became more liquid during the last decades (Chordia et al., 2011).

[17]Due to large sample size the feasible complexity of the applied type of standard error and estimation method is somewhat limited. For example stock-day double-clustered errors would mean to cluster along approximately 45,000 dimensions which typically leads to memory problems during the computation.

approaches to strengthen the validity of the results.

For each variable of interest, we estimate a second model containing the SMA indicator variables $SMAlong_{i,t}$ and $SMAshort_{i,t}$ instead of the SRL indicators. In the following, we present regression results for the liquidity measures as defined in Section 3.

5.1 Limit Order Book Depth

To analyze liquidity provision in the limit order book, we use an approach similar to Kavajecz and Odders-White (2004). Since we 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 EUR-volume in the book (e.g. x% of the daily average turnover) are less meaningful if only ten levels of the LOB are known and therefore would result in many missing or boundary values. We employ the measures *Depth5Ask*, *Depth5Bid*, *Depth5Imbalance* and *Depth10Imbalance* as defined in section 3 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 levels are active.

Insert Table 3 here.

Table 3 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 hypothesis H1b.

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 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, we find a significantly positive (negative) shift to the ask (bid) side of about 3.8% (-3.6%). If a support (resistance) level is present on level 6 to 10 of the limit order book, the estimate is also positive (negative) but of much smaller magnitude. This means the TA level is particularly related to depth close to this level and not to the overall depth on the respective side of the LOB. 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%).

Insert Table 4 here.

If traders submit orders in accordance to SRL the increase should already be visible in the LOB before the best bid or ask price reaches the respective support or resistance level. To assess whether this is the case, we estimate a model of type (1) for each order book level where we apply *Reldepth* as independent variable and use dummy variables (*TAlevel1*-*TAlevel10*) for active support (resistance) levels on the respective bid (ask) level as regressors. Furthermore, the control variables from model (1) are included.

Figure 2 illustrates the results for all 20 order book levels, i. e. 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 (TAlevel) on the same level. All estimates of TA indicators 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.

Insert Figure 2 here.

We refine the analysis of depth location by measures from Kavajecz and Odders-White (2004) to verify their results for our sample. This includes the measures *Askmode* (*Bidmode*) and *Askbalance* (*Bidbalance*). For LOB mode measures the distance (in EUR) to the nearest support (resistance) level is used as explanatory variable. In order to check whether depth peaks moves in accordance to the TA-level distance only observations with an active support or resistance in the book are considered. Table 4 shows the results. For the bid and ask side significantly positive estimates support this relation which confirms the results of Kavajecz and Odders-White (2004). Thus the distance to SRL can be used to approximate a location of increased depth in the LOB. The estimated relation between the variables seems to be weaker. An influencing factor certainly 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 0.2% to 0.5% compared to the unconditional standard deviation of *Bidbalance* and *Askbalance* of 12.6% and 12.9%, respectively.

Considering SMA signals, our hypotheses regarding depth and depth location are ambiguous since we assume that trading on moving average signals mainly influences liquidity demand. Hence liquidity supply could be adversely effected if liquidity supplier cannot adjust to the demand quickly. However this should only effect order book levels close to the best price. We repeat the above regression analyses using (aggregated) long and short signals from four SMA strategies. Results for measures of total depth and depth location are reported in Panel B of Table 3 and Table 4, respectively. For cumulative depth on the bid and ask side we find that for long and short signals depth is decreasing on both sides of the LOB. 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 liquidity 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 our 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 a midquote changes while order mode remains unchanged[18]. 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 SMA signals primarily drive liquidity demand and thereby affect the state of lower limit order book levels.

5.2 Trading Activity and Spread Measures

Table 5 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 marketable order volume decreases.

Insert Table 5 here.

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 which might be a sign that the effect is relatively weak. The effect size implies additional costs of EUR 0.32 to 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. A reason for increasing spreads might be the imbalance in limit buy and sell orders as our analysis of depth imbalances shows. Excess

[18]Controlling for midquote returns might not completely account for this effect since changes in mode are in absolute numbers. Note that in case of SRL, the TA distance variable includes the midquote change as well and thereby accounts for the move in mode.

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, we 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 we 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 7 we consider the aspect of price discovery and pricing errors in more detail.

Panel B of Table 5 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, we 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, we find no significant effect on effective spreads which contradicts hypothesis H1b.

Because the considered TA signals give a directional trading recommendation, we 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.

Insert Table 6 here.

Table 6, Panel A (Panel B) shows results for model specification of type (1) 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 price and afterwards 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[19]. Similarly, increased depth on SRL might cause quoted prices to be too high or low such that market orders in the same direction pay too much resulting in unfavorable short-run returns. Additionally, we perform the analysis for a 5-minute horizon which qualitatively yields the same results but smaller coefficient estimates. Although the shown evidence

[19]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).

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.

6 Informational Efficiency

The previous section shows that TA trading 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, we 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, we follow Comerton-Forde and Putninš (2015) and aggregate autocorrelations calculated over three frequencies to obtain a single measure. Therefore we apply a principal component analysis[20] to the three absolute autocorrelation series and take the first principal component as aggregate measure. 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

[20] The reasoning behind using the first principal component of the different autocorrelation horizons is to reduce measurement error of 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 less noise than a simple average of the inputs.

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, we use an inefficiency measure which captures the degree of predictability of stock returns by past market returns. If stock prices react to lagged market returns, the incorporation of market-wide information is less efficient for the stock (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. We 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 the both $R^2_{(2)}$ 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, we relate the above measures to the TA-based trading signals defined in Section 4. If TA-based trading has an effect on the degree of informational inefficiency, we expect the effect to 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, we accumulate the intraday SRL indicators *AtSupport* and *AtResistance*, *ResActiveL1-L5* and *SupActiveL1-L5*, as well as *SMAlong* and *SMAshort*. Note that we do not double count instances where a support and a resistance level is active in a single 1-minute interval. The resulting variables are called *AtSRL*, *LOB_SRL*, and *SMAsignals*, respectively. With the resulting stock-day panel, we estimate the following type of regression model, where $IM_{i,t}$ denotes one of our three informational efficiency measures for stock i on day t and analogously $TAcount_{i,t}$ one of the three TA count variables. The regression equation is defined as

$$IM_{i,t} = \beta \, TAcount_{i,t} + \sum_{j=1}^{6} \delta_j Control^{(j)}_{i,t} + \sum FE, \tag{2}$$

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. We estimate the above model for each informational efficiency measures and TA count variable.

Insert Table 7 here.

Table 7 shows the estimation results for all specifications of (2). 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[21] 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 MA 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.

[21] 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 MA 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.

7 Price Discovery

7.1 State Space Model (SSM) 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, we apply a state space model of midquote prices to analyze permanent and transitory price changes and volatility in relation to the TA signals defined in section 4. Since TA-based traders are assumed to be uninformed noise traders who potentially trade on the same side of the market, we expect price effects to be increasingly transitory around TA signals. To decompose prices into transitory and permanent parts, we use an adopted approach of the SSM methodology[22] introduced by Menkveld et al. (2007),

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

among others[23].

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

$$p_{i,t} = m_{i,t} + s_{i,t}, \tag{3}$$

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

$$m_{i,t} = m_{i,t-1} + \eta_{i,t}, \tag{4}$$

where η is a normally distributed error term with zero-mean and variance σ^2_η. We follow Brogaard et al. (2014) and Hendershott and Menkveld (2014) and assume an autoregressive process for the pricing error, i. e.

$$s_{i,t} = \phi s_{i,t-1} + \epsilon_{i,t}, \tag{5}$$

where ϵ is a Gaussian error term independent of η with zero mean and variance σ^2_ϵ.

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, we 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). We 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. we obtain estimates for the efficient

[23] See for example Menkveld (2013), Brogaard et al. (2014), and Hendershott and Menkveld (2014) for applications of the state-space approach in the context of price decomposition.

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, we 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.

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 we calculate the following ratios based on pricing error transitory innovation defined as

$$PEratio_{i,t} = \frac{|s_{i,t}|}{|s_{i,t}| + |\eta_{i,t}|} \quad \text{and} \quad TIratio_{i,t} = \frac{|\epsilon_{i,t}|}{|\epsilon_{i,t}| + |\eta_{i,t}|}. \tag{6}$$

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

7.2 SSM Estimation Results

Panel A of Table 8 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[24].

Insert Table 8 here.

Table 8, 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, we 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 we estimate a regression model containing only intercept and TA indicator variables and an extended model specification defined by

$$\begin{aligned} s_{i,t} = \alpha &+ \beta_1 TA1_{i,t} + \beta_2 TA2_{i,t} + \delta_1 \widetilde{VDAX}_{i,t} \mathbf{1}_{(s_{i,t}>0)} \\ &+ \delta_2 \widetilde{VDAX}_{i,t} \mathbf{1}_{(s_{i,t}<0)} + \delta_3 \widetilde{MCap}_{i,t} \mathbf{1}_{(s_{i,t}>0)} + \delta_4 \widetilde{MCap}_{i,t} \mathbf{1}_{(s_{i,t}<0)}, \end{aligned} \tag{7}$$

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 expect that market volatility is related to the size of pricing errors given the ratio of permanent and transitory effects is unchanged.

[24] The conditional volatility does not equal 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 we 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.

Thus, we 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 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).

Insert Table 9 here.

We 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[25].

Table 9 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 (6) are taken as independent variables. Thereby we 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 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 9 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 roughly 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

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

(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[26], the denomination through the permanent innovation component shows that relative values are slightly decreasing. We 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.

7.3 Discussion of SSM 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. In Section 5 we show that 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 makes this mechanism less likely, 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 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 (Shleifer and Summers, 1990; 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

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

direction of the signal vanishes.

Overall, both types of TA signals are associated with increased fluctuations in pricing errors supporting hypothesis H2b. In case of SMA the increase in permanent component outweighs the transitory part which contradicts the second part of H2b on permanent price changes. In Section 8 we present further evidence on the volatility of transitory and permanent price components on higher frequency which confirms the results of this section.

8 Robustness Tests

8.1 Liquidity Measures

To check the robustness of results presented in Section 5 we use two alternative approaches to test the relation between liquidity measures and TA indicator. First, we estimate models of type (1) for yearly subsamples to assess whether effects remain stable over time. The regression applies the same independent variables but we use standard errors double clustered by stock and day (Thompson, 2011). Additionally, we use an alternative approach to analyze liquidity measures. In a first step, we fit an auto-regressive model of the variables of interest for each stock-day. The model includes five lags and a quadratic 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, we do not include stock-day fixed effects. We also drop minutely fixed effects because the quadratic trend and the inclusion of lags incorporate the intraday variation structure. In sum, we estimate a model of type (1) 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 autoregressive characteristics in the analyzed liquidity measures.

Columns 2008 - 2013 of Table 10 show results for the measures turnover, quoted spread, effective spreads, Depth5 Ask, and Depth5 Bid for each year. For the sake of brevity the table contains solely the TA indicator estimates. Column 'All' shows results for the respective model of AR(5) residuals. The latter confirms 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, we find no significant SRL estimates in 2008 and relatively large estimates accompanied with high standard deviation in 2009. For effective spreads results are similar. 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. We interpret this results as additional evidence against hypothesis H1c.

8.2 Volatility of Transitory and Permanent Price Components

In Section 7, we use the SSM defined by equations (3), (4), and (5) 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 signal probably appears not instantaneously but is distributed over some period of time. Furthermore the approach of analyzing the size of (for example) pricing errors means we consider the mean effects in the price components instead of its variance. To complement the above analysis, we 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, we calculate the transitory volatility $\sigma_{s,i,t} = \sigma(s_{i,\tau}, ..., s_{i,\tau+59})$, where $\tau = 60t$ and , $t = 0, 1, ...$, in each 1-minute interval. Permanent volatility $\sigma_{w,i,t} = \sigma(w_{i,\tau}, ..., w_{i,\tau+59})$ is defined analogously. From the pooled stock-minute volatilities and volatility ratios $100 * \sigma_{s,i,t}/(\sigma_{s,i,t} + \sigma_{w,i,t})$, we estimate regression models including SRL and SMA indicators, respectively, and a second specification adding VDAX (market volatility) and market capitalization. All models use stock-day fixed effects and double clustered standard errors.

Table 7 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 but considering 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[27]. Obviously, this is caused by the reduction in permanent volatility. For SMA signals the transitory and permanent volatility derived from the SSM increases significantly. The effect is more dominant for permanent volatility as the

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

decreasing share (about 4%) of transitory volatility indicates.

Overall, the SSM applied to 1-second midquote data confirms the results presented in Section 7. 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. We 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, hence respective tables are omitted.

9 Conclusion

We demonstrate that two popular TA trading heuristics are related to significant variations in market quality measures. In 1-minute intervals with an active SRL we find significant increases in limit order supply as well as higher quoted and effective spreads (hypotheses H1a/H1c). In case of SMA signals, turnover and quoted spreads rise significantly (hypotheses H1b/H1c). Although effective spreads are not significantly higher, we 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 TA traders implying that trading on TA signals is not beneficial from a short-run perspective. In sum, the empirical evidence confirms hypotheses H1a and H1b, whereas hypothesis H1c is rejected. In this regard, the results for Xetra contradict findings from other studies.

The analysis of SSM price components shows that TA trading signals are related to differences in permanent and transitory price components (Hypothesis H2b). 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. For SMA signals we 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 TA signals contain no fundamental information about some stock and are not systemically related to external idiosyncratic information events, our 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 we 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 TA 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 indications of the ongoing competition between TA noise traders and other market participants.

10 Figures and Tables

Table 1: 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

Table 2: Technical Trading Signals. The table shows the number support and resistance levels determined by the smoothing algorithm described in Section 4 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

Table 3: Depth and Depth Balance Regressions. This table shows regression results for depth measures regressed on SRL and MA dummy variables as specified in equation (1). 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 deviations 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)

Table 4: 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 (1). *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 deviations 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)

Table 5: Regression Models for Liquidity Measures. The table presents estimation results from the panel regressions defined by equation (1). 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 deviations are given 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)

Table 6: Realized Spreads and Price Impacts of Buy and Sell Orders. The table presents estimation results from the panel regressions defined by equation (1). 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 deviations 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)

Table 7: 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 deviations 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 8: State Space Model Estimation. The table shows summary statistics based on the output of the state space model defined by (3),(4), and (5). 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 9: 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),(4), and (5). 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 (7). All models contain standard errors double-clustered on stock and day. *, **, *** denote significance on a 10%, 5%, and 1% level, respectively. Standard deviations 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)	(0.0006)		(0.0006)	
At support		-0.3147***	-0.3434***	4.4104***	3.3983***	3.5426***	2.7115***
		(0.0236)	(0.0227)	(0.0236)	(0.0005)	(0.0236)	(0.0005)
At resistance		0.2901***	0.3226***	4.8947***	4.0136***	3.8778***	3.1482***
		(0.0202)	(0.0208)	(0.0202)	(0.0227)	(0.0202)	(0.0227)
	$\times\mathbf{1}_{s_{i,t}>0}$		0.6173***				
VDAX			(0.0658)		0.8189***		0.7168***
	$\times\mathbf{1}_{s_{i,t}<0}$		-0.6244***		(0.0208)		(0.0208)
			(0.0658)				
	$\times\mathbf{1}_{s_{i,t}>0}$		-0.0420				
Market cap			(0.0998)		-0.6511**		-0.4000
	$\times\mathbf{1}_{s_{i,t}<0}$		0.0411		(0.0658)		(0.0658)
			(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)	(0.0005)		(0.0005)	
SMA long		0.8931***	0.8636***	-1.4830***	-1.5624***	-2.3190***	-2.3867***
		(0.0637)	(0.061)	(0.0637)	(0.0005)	(0.0637)	(0.0005)
SMA short		-0.9583***	-0.9308***	-1.6344***	-1.7104***	-2.4301***	-2.4936***
		(0.0801)	(0.0778)	(0.0801)	(0.061)	(0.0801)	(0.061)
	$\times\mathbf{1}_{s_{i,t}>0}$		0.6217***				
VDAX			(0.0682)		9.2606***		7.5421***
	$\times\mathbf{1}_{s_{i,t}<0}$		-0.6310***		(0.0778)		(0.0778)
			(0.0682)				
	$\times\mathbf{1}_{s_{i,t}>0}$		-0.0003				
Market cap			(0.0317)		-1.5640**		-1.4001**
	$\times\mathbf{1}_{s_{i,t}<0}$		-0.0025		(0.0682)		(0.0682)
			(0.032)				
Fixed effects		no	no	no	yes	no	yes

Table 10: 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 (1) 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 deviations 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)

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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)

Table 11: 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 denote the 1-minute standard deviation of the respective price components of SSM (3),(4), and (5) 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 deviations 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)	(0.0055)	(0.0055)
At Resistance	0.0056	0.0057	-0.0868***	-0.0833***	6.4049***	6.3664***
	(0.0038)	(0.0038)	(0.0084)	(0.0082)	(0.0038)	(0.0038)
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)	(0.0044)	(0.0044)
SMA short	0.0168***	0.0167***	0.2939***	0.2926***	-3.9555***	-3.9490***
	(0.0046)	(0.0046)	(0.0158)	(0.0158)	(0.0046)	(0.0046)
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)

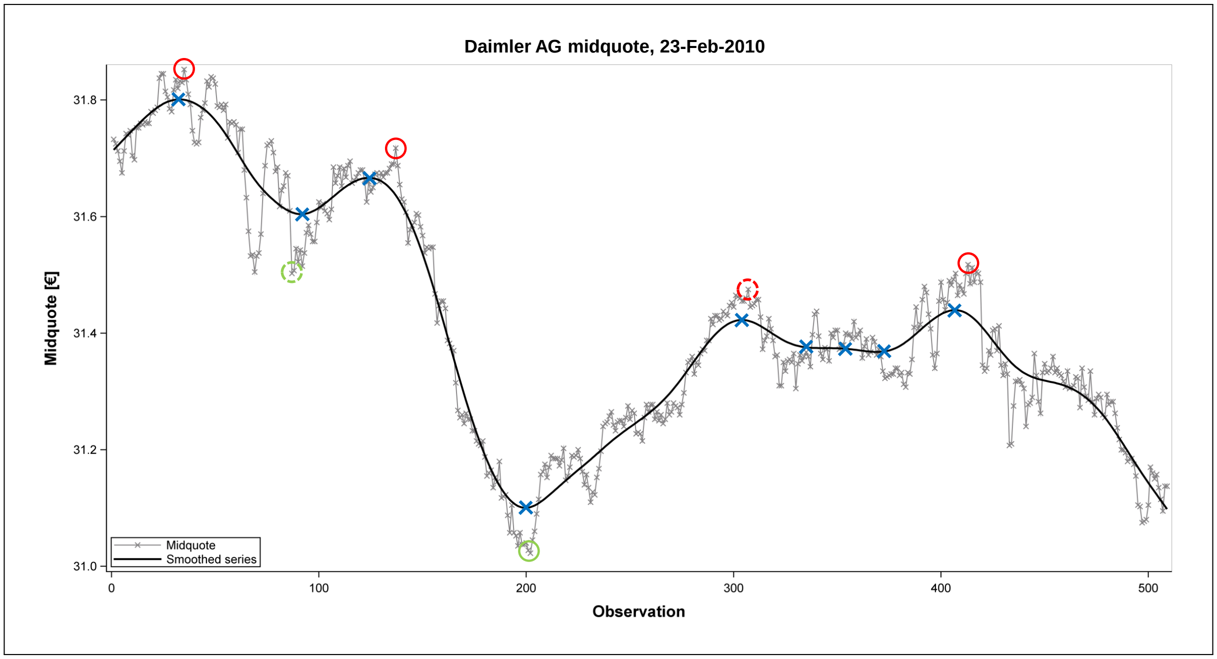

Figure 1: Visualization of the Smoothing Algorithm.

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, respectively. Dashed circles (first low and third high) do not meet the requirement being more extreme than subsequent extrema and are not considered.

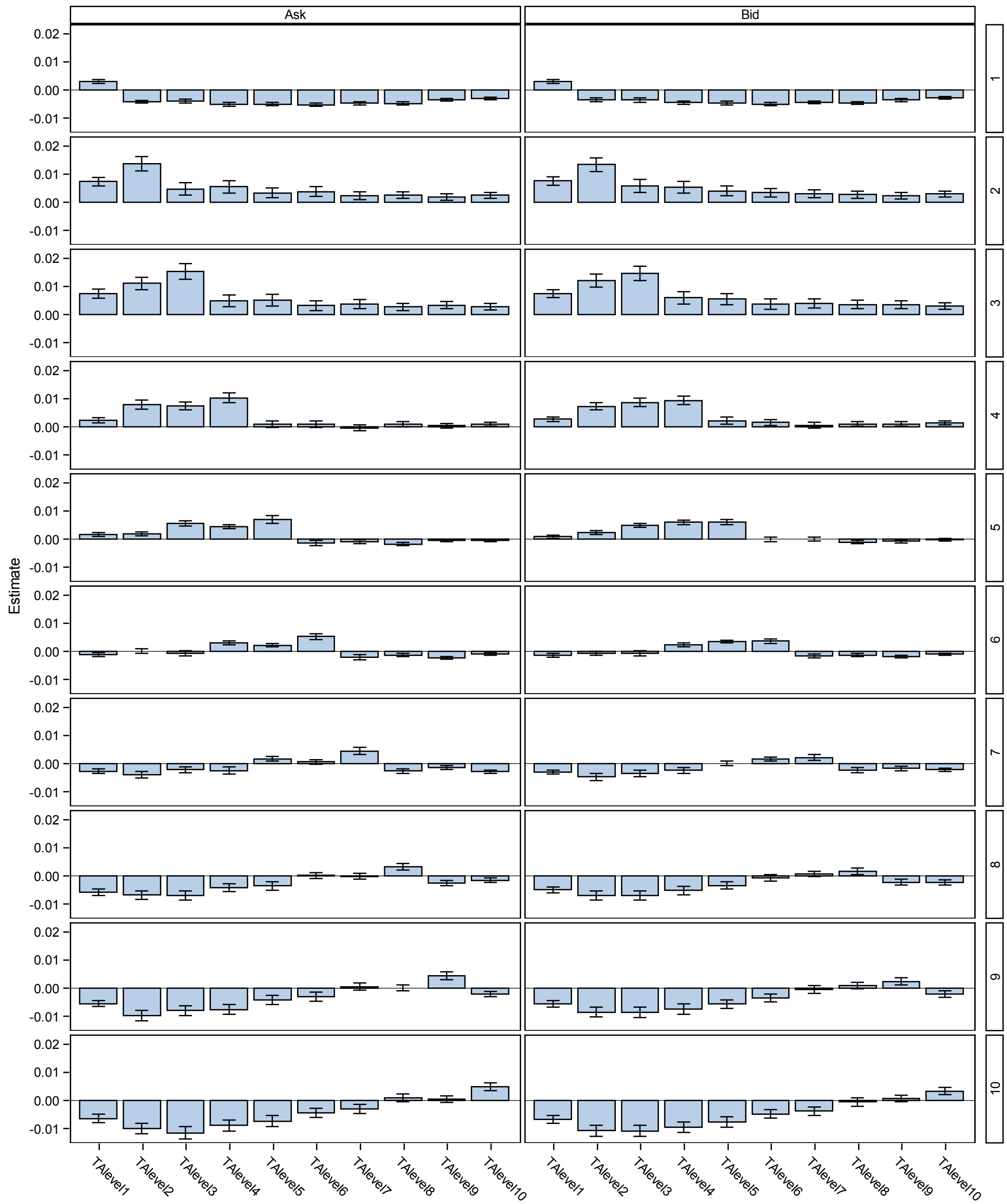

Figure 2: Limit Order Book Depth on Support and Resistance Levels.

This figure depicts the coefficient estimates of regression models of relative depth on each limit order book level on the ask and bid side. Relative depth is defined as $\frac{Depth_{i,t}(j)}{\sum_{k=1}^{10} Depth_{i,t}(k),}$ where $Depth_{i,t}(j)$ denotes the depth (in EUR) on the j-th level in stock i at time t calculated for bid and ask side separately. In addition to the control variables used in (1), dummies signaling active support (resistance) levels on a certain bid (ask) level 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.

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