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ORIGINAL ARTICLE

Bid-Ask Spread Patterns and the Optimal Timing for Discretionary Liquidity Traders on Xetra

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Abstract This paper explores the statistical and economical significance of intraday and -week patterns in bid-ask spreads. We investigate a large panel of high frequency data for stocks traded on the XETRA trading platform and observe significant patterns in spreads. In addition to showing the robustness of our findings over time, as well as in cross-section, we are also able to demonstrate the patterns' predictability in an out-of-sample approach. Our findings have clear implications, especially for uninformed but discretionary liquidity traders, which allow significant and economically relevant reductions of transaction costs.

Keywords Intra-day · Bid-ask spread · Liquidity · Timing · Discretionary trader

JEL Classification G10 · G14

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1 Introduction

With the implementation of MiFID I in 2007 and furthermore with the upcoming implementation of MiFID II, the European Union aims to harmonise and regulate investment services in the member states, as well as in Iceland, Norway and Liechtenstein.[1] The directive is intended to increase competition and consumer protection for investment services. One of the primary measures intended to enhance consumer protection involves regulations governing best execution of trades. Under MiFID, firms are required to take all reasonable steps to obtain „the best possible result" in the execution of a client's order. Investment management firms also have a fiduciary responsibility to act in their clients' best interests and are obliged to seek best execution for every trade.[2] The *best possible result* includes not only the execution price but also the cost, speed, likelihood of execution, likelihood of settlement, and any other factors deemed relevant. This implies that not only explicit costs, such as commission fees, but also implicit trading costs, such as bid-ask spreads or the price impact, need to be considered by asset managers.

The group of traders we examine are discretionary liquidity traders. Since the seminal paper of Admati and Pfleiderer (1988), the crucial role of such traders has been widely acknowledged by the academic finance literature. Discretionary liquidity traders are investors who have an exogenous need to trade; however, they can choose the timing of their transactions strategically to minimise the expected trading costs. This particularly applies to large institutional traders, such as mutual funds or pension funds, who experience trading needs, for example, due to liquidity needs of their clients or for portfolio-rebalancing reasons. In this paper, we analyse the potential savings related to bid-ask spreads that can be realised by discretionary liquidity traders who predict the optimal time to trade in an order-driven market to minimise the related costs. We investigate intra-day and inter-day spread patterns for a large panel of German stocks traded on the Xetra system. As outlined by Krogmann, Michael (2011), in Xetra Institutional Equity, implicit trading costs may account for up to 80% of the overall costs of a trade. Stoll (2000) and Huang and Stoll (1997) argue that bid-ask spreads serve as a proxy for the total friction and hence reflect cost components such as order processing, inventory and adverse selection costs. Therefore, we are convinced that our investigation has valuable normative implications, especially for discretionary liquidity traders seeking best execution in order-driven markets, even though we neglect other implicit trading costs, such as the price impact of orders.

[1] MiFID I replaced the Investment Services Directive (ISD) in November 2007. MiFID II will be in force on the 3rd of January 2018.

[2] See, for example, „Trade management guidelines" by the CFA Institute: http://www.cfapubs.org/doi/pdf/10.2469/ccb.v2004.n3.4007.

[3] Imagine the letter „J" mirrored along the vertical axis. In other words, the spread has the highest value on the left side of the x-axis, declines going to the right and increases by a smaller amount further to the right at the end.

Our empirical results suggest that intra-day bid-ask spread patterns are reverse J-shaped[3] and are significant statistically and economically. In contrast, we observe the inter-week pattern of bid-ask spreads to be U-shaped and both less pronounced than the intra-day pattern and economically less significant. Most practically important is the finding that such patterns are stable over time and in cross-section, enabling discretionary liquidity traders to predict and exploit them.

The contributions of our paper are threefold. First, to the best of our knowledge, we are the first to analyse such a large panel of intra-day data. While usual intra-day analyses explore weeks or at best months of data and often examine only a few stocks (e.g., the constituents of the DAX30 index), we examine the time span of over seven years and 267 stocks. That allows us to be the first to test the robustness of observed bid-ask spread patterns over time, e.g., before the crisis and during the three years of the crisis, and for different subsets of stocks, including the DAX30 stocks and small caps vs. large caps. Second, our analysis not only focuses on the statistical significance but also investigates the economic significance of intra-day and inter-week liquidity patterns. This allows us to quantify the savings potential for discretionary liquidity traders. Third, we test the predictability of bid-ask spread patterns in an out-of-sample study, which has valuable practical implications for discretionary liquidity traders. We also show with this study that a simple trading strategy can attain an economically significant gain. This underscores the importance of our results as being more than merely a statistical artefact.

2 Literature review

The existing literature offers several theoretical foundations for intra-day and intra-week liquidity patterns. First, Admati and Pfleiderer (1988) develop a theory in which an intra-day pattern in liquidity arises endogenously as a result of the interaction of liquidity and informed traders. In the resulting model, informed traders act on the basis of superior information, while liquidity traders have an exogenous desire to trade immediately. The main innovation is the introduction of discretionary liquidity traders, who exercise discretion as to the timing of their transactions. Admati and Pfleiderer (1988) determine that informed and discretionary liquidity traders cluster in the same intra-day periods, explaining the empirically observed U-shaped pattern of the trading volume. Other studies observe that the use of trading algorithms leads to specific intra-day patterns (Almgren and Chriss 2001 and Hora 2006), while Heston et al. (2011); Heston, Korajczyk, Sadka, and Thorson (2011) argue that patterns could be explained by clustered trading of active managers and institutional traders at specific times of day. The latter is supported by Heston et al. (2010); Heston, Korajczyk, and Sadka (2010), showing that bid-ask spreads, volume, volatility, order imbalance and stock returns follow half-hour patterns.

Foster and Viswanathan (1990) introduce a model that can explain inter-day regularities in transaction costs. They observe that trading costs are the highest on Mondays, as informed traders have superior information at the beginning of the week due to extra information accumulated during the weekend. Foster and Viswanathan (1993) examine a sample of NYSE- and AMEX-traded stocks in 1988 and observe adverse selection costs to be lowest during the middle of the trading day and higher at the beginning, as well as towards the close, of trading. Moreover, they observe patterns consistent with their previous study, as adverse selection costs are higher on Mondays than on other days.

By determining whether a spread quote for an NYSE-traded stock is from a specialist, the limit order book, or both, Chung et al. (1999) analyse the effect of limit orders on NYSE spreads. They observe that spreads determined by limit order traders follow a U-shaped intra-day pattern, in contrast to bid-ask spreads of specialist-driven quotes, which are highest at the beginning of the trading day, decline later in the morning and then level off, thus deviating from a U-shaped pattern. McInish and Van Ness (2002) decompose the bid-ask spread of 30 NYSE- and regional exchange-listed stocks of the Dow Jones Industrial Average (DJIA) index into its components, the order-processing cost and the asymmetric information cost. The authors determine that time-of-day dummy variable coefficients for bid-ask spreads show an approximately J-shaped pattern as in McInish and Wood (1992); however, only four of 12 intra-day dummy variables are significant at the 5% level. Vo (2007) uses the standardised quoted spread as a tightness measure for stocks traded on the Toronto Stock Exchange (TSE). This researcher observes that intra-day bid-ask spreads are U-shaped, confirming the pattern observed in specialist markets by Chan et al. (1995) and Chung et al. (1999). The U-shaped intra-day bid-ask spread pattern is explained by the accumulation of overnight information by the morning, as in the evening, there is a period of non-trading overnight.

Gomber et al. (2015); Gomber, Schweickert, and Theissen (2015) analyse the intra-day liquidity of 21 stocks traded on Xetra, measuring it via the quoted bid-ask spread and the Exchange Liquidity Measure (XLM). Similar to the finding of Vo (2007), the intra-day pattern of bid-ask spreads and the XLM pattern are both U-shaped. Hussain (2011) examines proportional bid-ask spreads and the trading volume of DAX30 constituents. The researcher reports a J-shaped pattern of intra-day proportional bid-ask spreads with a bump following the intra-day auction at 1:00 p.m., which seems to induce higher bid-ask spreads. This finding contradicts the often-reported U-shaped pattern, e.g., observed by Gomber et al. (2015); Gomber, Schweickert, and Theissen (2015) and Brock and Kleidon (1992), but is consistent with patterns reported by McInish and Wood (1992). Kempf and Mayston (2008) analyse the common features of intra-day liquidity of Xetra-listed DAX30 stocks. All proxies for liquidity are observed to have significant co-variation, while the commonality increases with the the order book volume taken into account. Ultimately, Kempf and Mayston (2008) conclude that commonality in liquidity is a result of correlated trading by market participants.

Roll (1984), Choi et al. (1988), Glosten and Harris (1988), Hasbrouck (1988), Stoll (1989), George et al. (1991); George, Kaul, and Nimalendran (1991), Huang and Stoll (1997) and Madhavan et al. (1997); Madhavan, Richardson, and Roomans (1997) decompose the spread and observe it to be significantly influenced by, in addition to other factors such as order processing and inventory holding, the information asymmetry in the market, as also shown theoretically by Glosten and Milgrom (1985), Gong (2007), Gregoriou et al. (2005); Gregoriou, Ioannidis, and Skerratt (2005) and Huang and Stoll (1997). Therefore, if information asymmetry is the driving factor, the spread is expected to be the highest at the opening and the closing and probably increasing to some degree after lunch, resulting in a reversed m-shaped spread pattern [4], which is confirmed empirically by Heston et al. (2010); Heston, Korajczyk, and Sadka (2010), Heston et al. (2011); Heston, Korajczyk, Sadka, and Thorson (2011) and Garvey and Wu (2009). A higher spread is not necessarily a reason to avoid trading, as many traders do not have the flexibility to choose their trading times. In this case the combination of the execution speed and execution cost is important, as the two factors exhibit offsetting time-varying patterns during the course of a trading day. Garvey and Wu (2010) seek to determine the optimal, in terms of being fast and cheap, times to trade U.S. equities. The authors observe that marketable (non-marketable) orders submitted around the open are more likely to exhibit the best combination of low cost and high-speed execution.

In conclusion, in addition to theoretical approaches, there is substantial empirical support for stable liquidity patterns in various stock exchanges around the world. Early studies of stock liquidity analysed daily data, whereas the more recent literature examines intra-day data, i.e., intra-day bid-ask spread patterns in specialist- and order-driven markets. Several researchers characterise the observed bid-ask spread patterns as being either J-, U- or reverse m-shaped. We will contribute to this literature by examining the German Xetra market, focusing on tick-by-tick data to identify spread patterns and, furthermore, to explore the possibility of exploiting such patterns if the timing of trades is sufficiently flexible.

3 Data

This study uses tick-by-tick data from the Karlsruher Kapitalmarktdatenbank (KKMDB), which provides data from Deutsche Boerse AG for research purposes. We combine continuous best bid and ask prices with transaction data and aggregate them into a minute-by-minute time series for each stock. In doing so, we compute the equally weighted average of best bid and best ask prices for each stock during each one-minute interval. The period under consideration is from 1st February 2002 until 30th September 2009 and comprises all German stocks listed on Xetra at this time. As a result, the dataset consists of 1226 stocks listed on XETRA for a maximum of 1950 trading days. Each trading day, lasting from 9:00 a.m. to 5:30 p.m., is subdivided into 510 successive one minute-long intra-day intervals. Trading costs are measured via the quoted relative bid-ask spread as shown in Eq. (1), averaged over all quotes in the limit-order book during each one minute-long interval per stock i:

$$\mathrm{BAS}_{i,t} = \frac{P_{i,t}^{A} - P_{i,t}^{B}}{(P_{i,t}^{A} + P_{i,t}^{B})/2} \tag{1}$$

[4] Imagine the letter „m“ mirrored along the horizontal axis. The result is a pattern with peaks on the left, in the middle and on the right, and valleys in between.

where

$BAS_{i,t}$ the relative bid-ask spread of stock i at time t;

$P_{i,t}^{A}$ the best ask quote of stock i at time t;

$P_{i,t}^{B}$ the best bid quote of stock i at time t.

Since not all stocks are continuously traded or irregular and erroneous data may exist, several filter criteria are applied to extract a meaningful dataset for the 1226 stocks listed on XETRA during the sample period. First, observations with negative bid-ask spreads are excluded following a common approach of studies analysing intra-day data. We have also checked for positive outliers and identified three large but not entirely impossible spreads. Because of this and the low number compared to the total number of observations, we left them in the dataset. To avoid influence from the most thinly traded stocks, we only include days and stocks with at least 100 quoted bid-ask spreads on at least 100 trading days during the sample period. As a result, 267 stocks remain in our sample, with the total number of observed bid-ask spreads being 80 638 414.

4 Empirical Results

4.1 Statistical Significance

Due to limited computational resources, we cannot use all of the 80 638 414 observations mentioned in Sect. 3 to test the statistical significance of intra-day and intra-week patterns. Instead, we compute the equally weighted average for each stock during each trading minute $m = 1, ..., 510$ on each trading day $d = 1, ..., 5$. As a result, the analysed time series of relative bid-ask spreads is reduced to the maximum of $d \cdot m = 5 \cdot 510 = 2550$ observations per stock. With our sample containing 267 stocks, the result is an unbalanced panel of 680 223 relative bid-ask spreads. Consequently, $BAS_{i,t}$ is the relative bid-ask spread of stock i during the one-minute intra-day interval m on weekday d. For notational convenience, index t is introduced to replace the two time indexes m and d. We are convinced that this simplification has no detrimental effect on the normative value of our analysis, as discretionary traders can rather choose the time of the day or the day of the week at which they trade than select a distinct month or even a year. In what follows, when testing the out-of-sample predictability in Sect. 4.4, we use the full initial dataset with all 80 638 414 observations.

Our analysis starts with a plot of the cross-sectional mean and median relative bid-ask spread on each individual trading day. The panel on the left-hand side of Fig. 1 shows a U-shaped intra-week spread pattern. This implies that the average relative spread is lowest on Wednesdays and highest on Mondays and Fridays. This pattern is clearly observable for the mean as well as for the median; however, the magnitude of the intra-week spread differences seems rather low. The plot on the right-hand side of Fig. 1 depicts the cross-sectional standard deviation of spreads on each trading day. It shows that the dispersion of relative bid-ask spreads is highest during Mondays and Tuesdays.

Figure 2 includes intra-day plots of the cross-sectional mean and median spreads (the left-hand side) and the cross-sectional standard deviation (the right-hand side). The illustration on the left-hand side indicates a clearly reversed J-shaped intra-day pattern in relative bid-ask spreads. The mean and median spread is highest during the initial minutes of a trading day and steadily declines during the first three trading hours. A bump in spreads can be observed around the midday auction at 1:00 p.m., before spreads again increase during the final trading minutes.[5] The right chart of Fig. 2 shows that the cross-sectional dispersion of spreads decreases during the initial trading hours of a day, although the entire intra-day pattern is characterized by clear volatility clustering.

While Figs. 1 and 2 exhibit clear intra-week, as well as intra-day, patterns of relative bid-ask spreads, we still need to test statistical significance. As the cross-sectional variation in spreads is observed to be quite large in comparison to the mean and the median, our methodology considers potential cross-sectional differences in bid-ask spreads. We do so by estimating the fixed-effects panel model outlined in Eq. (2). Employing the in-sample estimator allows us to account for unobservable time-invariant stock-specific determinants of the bid-ask spread. To analyse the in-sample statistical significance of intra-day and intra-week patterns, we regress the bid-ask spread of stock $i = 1, ..., 267$ during minute $t = 1, ..., 2550$ on 509 one-minute interval-specific dummies and 4 weekday-specific dummies:

$$\mathrm{BAS}_{i,t} = \sum_{j=2}^{510} \beta_j \cdot \mathrm{DUM}_j^M + \sum_{k=2}^{5} \gamma_k \cdot \mathrm{DUM}_k^W + c_i + u_{i,t} \tag{2}$$

where

$\mathrm{BAS}_{i,t}$	relative-bid-ask spread of stock i during minute t;
DUM_j^M	509 binary variables that equal 1 during minute j and zero otherwise;
DUM_k^W	4 binary variables that equal 1 on weekday k and zero otherwise;
c_i	fixed-effects in cross-section;
$u_{i,t}$	the residual of firm i during minute t.

In our analysis, coefficients β_j measure the intra-day difference of the bid-ask spread relative to the bid-ask-spread of the first trading minute, while γ_k measures the intra-week difference in spreads relative to Monday.

When estimating Eq. (2), the average of cross-sectional fixed-effects equals 0.0136 with the standard deviation of 0.0050. Within the framework of the estimated model, this implies that the cross-sectional mean of relative bid-ask spreads during the first trading minute on Monday is 136 basis points. We report estimates for weekday dummies in Table 1. It shows that the spread is significantly lower on Tuesdays, Wednesdays and Thursdays. However, the magnitude of the observed

[5] In what follows, we report results including spreads during the midday auction. Table 4 of the Appendix shows that omitting the midday auction changes our results only very marginally.

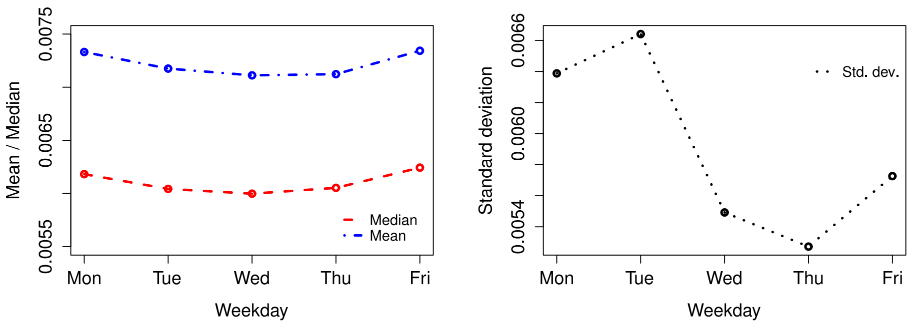

Fig. 1 The left-hand side figure shows the intra-week levels of the mean and median relative bid-ask spread. The plot on the right-hand side shows the cross-sectional standard deviation of the relative bid-ask spread on each trading day

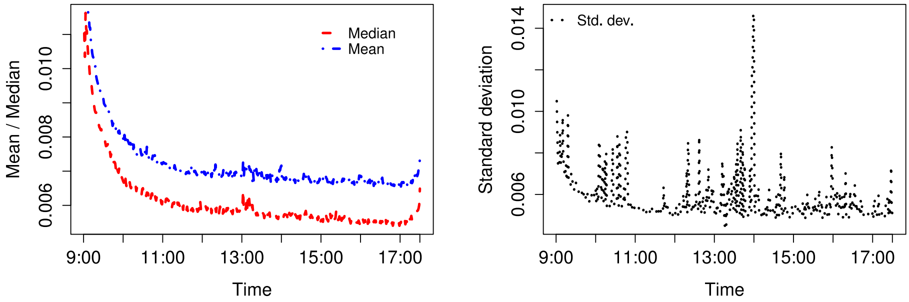

Fig. 2 The left-hand side figure shows the cross-sectional mean and median relative bid-ask spread for each minute of a trading day. The plot on the right-hand side depicts the intra-day dynamics of the cross-sectional standard deviation of the relative bid-ask spread

Table 1 Estimated γ_k coefficients of Eq. (2)

	estimate	t-stat
γ_1 [Tue]	−0.00016***	−6.9896
γ_2 [Wed]	−0.00023***	−11.7871
γ_3 [Thu]	−0.00022***	−10.4610
γ_4 [Fri]	0.00000	0.2103
R^2_{adj}	0.0994	
cross-sectional dimension	267	
time series dimension	2532–2550	
total observations	680 223	

*** denotes statistical significance at the 1% level. For convenience of illustration, β_j coefficients are not included in this Table and instead are graphically illustrated in Fig. 3

difference is rather low, reaching the maximum of 2.3 basis points on Wednesdays. Nevertheless, we conclude that the sample in our study exhibits a statistically significant U-shaped intra-week pattern of relative bid-ask spreads.

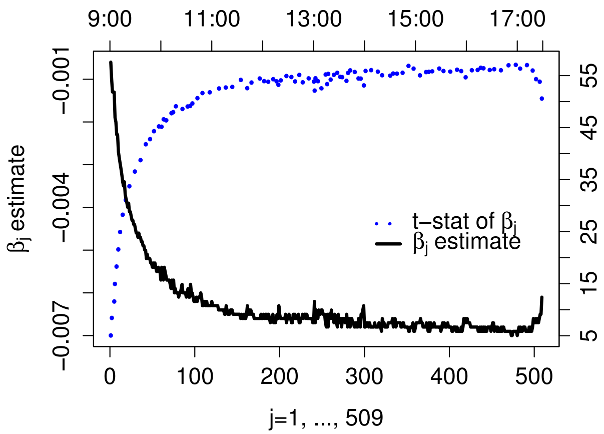

Fig. 3 This figure illustrates the estimates of β_j on the left axis and respective test statistics on the right axis

The estimated coefficients and the corresponding test statistics of 509 intra-day dummy variables are reported in Fig. 3. It shows that all estimated β_j coefficients are negative and statistically significantly different from zero, indicating a decline in relative bid-ask spreads throughout a trading day. Specifically, a steep decline in spreads is observed during the first 150 minutes of a day. Later in the day, around the intra-day auction at 1:00 p.m., the estimated coefficients fluctuate considerably. The maximum difference of 70 basis points, corresponding to a reduction of the average opening spread by more than half, is observed exactly 480 minutes after trading begins. During the last 30 minutes, between 5:00 p.m. and 5:30 p.m., spreads increase, though only by approximately 5 basis points. We conclude that the examined data exhibit a statistically significant reverse J-shaped intra-day pattern of relative bid-ask spreads. This pattern's potential economic significance and out-of-sample predictability will be explored in Sect. 4.3 and 4.4. However, we first test the robustness of our findings.

4.2 Robustness of Bid-Ask Spread Patterns

To test the robustness and to increase the applicability of our findings for practitioners, we perform regressions again for different groups of stocks (e.g., DAX30, large caps and small caps), different time frames (before and during the crisis) and with and without the midday auction. In what follows, we report the most important results. A sample overview is shown in Table 11.

We observe that omitting the midday auction from the dataset does not substantially affect our results (see Table 4 and Fig. 5). Nevertheless, we also excluded the midday auction while performing all robustness tests. This finding is unsurprising, as the number of excluded minutes is small and, therefore, so is its influence on the regression results. According to Xetra.com, currently only approximately 2% of the total daily volume of DAX shares are traded via the intra-day auction.

Examining the DAX30 stocks, we interestingly observe that the bid-ask spread pattern of weekdays retains the same shape (see Table 5); however, the estimates decline below 1 basis point. It seems that the pattern might still exist in very liquid

Table 2 The economic significance of intra-day spread patterns. Columns I and II show the absolute savings potential. It is represented by summary statistics of the absolute differences between the maximum (column I) or mean (column II) intra-day bid-ask spread and the spread during the optimal ten-minute interval. Columns III and IV show the relative savings potential. Column III provides summary statistics for the difference between the maximum and the minimum intra-day spreads relative to the maximum spread, while column IV shows the respective statistics for the difference between the mean and the minimum intra-day spread relative to the mean spread

	(I)	(II)	(III)	(IV)
	Absolute savings potential		Relative savings potential	
	Max − Min	Mean − Min	$\frac{\text{Max}-\text{Min}}{\text{Max}}$	$\frac{\text{Mean}-\text{Min}}{\text{Mean}}$
Min	0.0004	0.0000	0.2173	0.0385
Max	0.0423	0.0086	0.8220	0.4392
Std. dev.	0.0040	0.0010	0.1184	0.0416
Mean	0.0061	0.0011	0.5233	0.1451
t-stat	(24.801)	(18.126)	(72.107)	(56.954)

Table 3 A summary of the out-of-sample predictability of intra-day bid-ask spread patterns. We determine, separately for each stock, the ten-minute interval with the lowest bid-ask spread by computing equally weighted average bid-ask spreads for 51 intra-day intervals during the preceding 100 trading days. The intra-day interval with the lowest average spread is used to compute the predicted minimum spread on the next trading day, $\widehat{\text{Min}}$. In Panel A, we provide the summary statistics of the absolute deviation (in columns I and II) and the relative deviation (in columns III and IV) of $\widehat{\text{Min}}$ from the maximum (max) and average (mean) bid-ask spread during each predicted trading day. In Panel B, we focus on the stability of the predictability over time and in cross-section by providing the number of days and the number of firms with positive and negative predicted savings. The data sample analysed by this study is an unbalanced panel of 267 stocks over 1850 trading days, with a total of 230 890 observations

Panel A	(I)	(II)	(III)	(IV)
	Absolute predicted savings		Relative predicted savings	
	Max − $\widehat{\text{Min}}$	Mean − $\widehat{\text{Min}}$	$\frac{\text{Max}-\widehat{\text{Min}}}{\text{Max}}$	$\frac{\text{Mean}-\widehat{\text{Min}}}{\text{Mean}}$
Pooled 1st quart.	0.0021	−0.0002	0.4921	−0.0689
Pooled mean	0.0068	0.0004	0.6130	0.1228
Pooled median	0.0046	0.0003	0.6412	0.1600
Pooled 3rd quart.	0.0086	0.0011	0.7641	0.3659
Pooled std. dev.	0.0110	0.0030	0.2008	0.3695
Panel B	(V)		(VI)	
	Average savings		Median savings	
# of days with positive absolute savings	1774		1849	
# of days with negative absolute savings	76		1	
# of firms with positive absolute savings	255		264	
# of firms with negative absolute savings	12		3	

Table 4 Estimates of γ_k coefficients in Eq. (2) for all stocks without the midday auction period

	estimate	t-stat
γ_1 [Tue]	−0.00016***	−6.9598
γ_2 [Wed]	−0.00023***	−11.7077
γ_3 [Thu]	−0.00021***	−10.3554
γ_4 [Fri]	0.00000	0.1390
R^2_{adj}	0.1044	
cross-sectional dimension	267	
time series dimension	2385–2400	
total observations	640 199	

*** denotes statistical significance at the 1% level

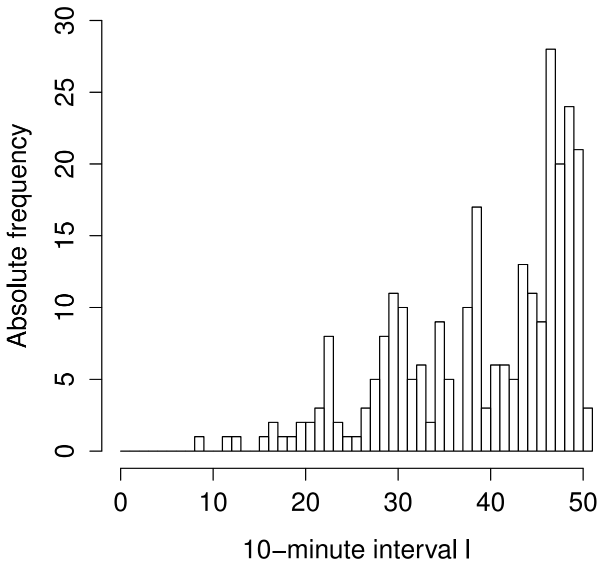

Fig. 4 The cross-sectional distribution of ten-minute intra-day intervals with the lowest relative bid-ask spreads

Table 5 DAX30 WITHOUT MIDDAY AUCTION – Estimates of γ_k coefficients in Eq. (2)

	estimate	t-stat
γ_1 [Tue]	−0.00004***	−6.1995
γ_2 [Wed]	−0.00005***	−6.7596
γ_3 [Thu]	−0.00002***	−3.1924
γ_4 [Fri]	0.00000	0.3425
R^2_{adj}	0.6485	
cross-sectional dimension	35	
time series dimension	2390–2400	
total observations	83 990	

*** denotes statistical significance at the 1% level

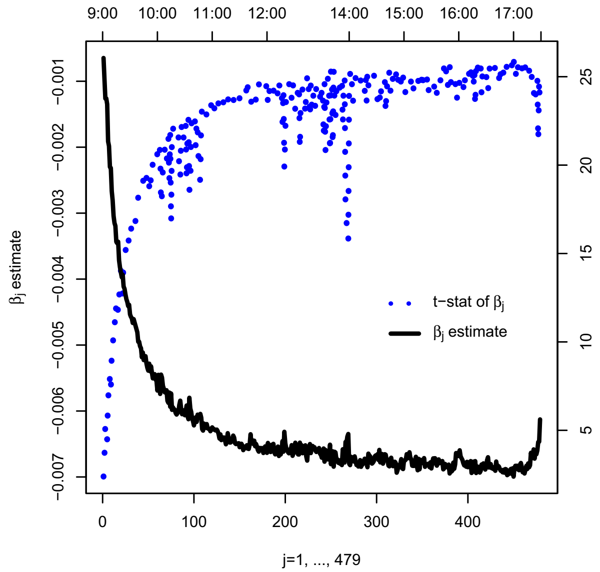

Fig. 5 This figure illustrates the estimates of β_j for all stocks without the midday auction period on the left axis and respective test statistics on the right the right axis

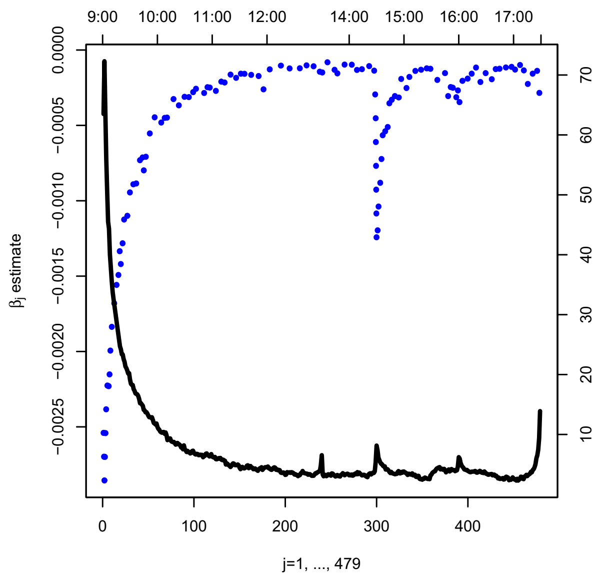

Fig. 6 This figure illustrates the estimates of β_j for DAX30 stocks without the midday auction period on the left axis and respective test statistics on the right axis

markets, while not being practically exploitable. The same holds for the intra-day pattern, which retains a shape similar to that observed above but with very low estimates that seem to not be exploitable (see Fig. 6).

Table 6 LARGE CAP WITHOUT MIDDAY AUCTION – Estimated γ_k coefficients in Eq. (2)

	estimate	t-stat
γ_1 [Tue]	−0.00015***	−4.5102
γ_2 [Wed]	−0.00026***	−13.2345
γ_3 [Thu]	−0.00021***	−10.2702
γ_4 [Fri]	−0.00007***	−3.3719
R^2_{adj}	0.0638	
cross-sectional dimension	134	
time series dimension	2390–2400	
total observations	321 404	

*** denotes statistical significance at the 1% level

Table 7 SMALL CAP WITHOUT MIDDAY AUCTION – Estimated γ_k coefficients in Eq. (2)

	estimate	t-stat
γ_1 [Tue]	−0.00018***	−5.7966
γ_2 [Wed]	−0.00019***	−6.3780
γ_3 [Thu]	−0.00022***	−6.8146
γ_4 [Fri]	0.00008**	2.4404
R^2_{adj}	0.1579	
cross-sectional dimension	133	
time series dimension	2385–2400	
total observations	318 795	

*** denotes statistical significance at the 1% level

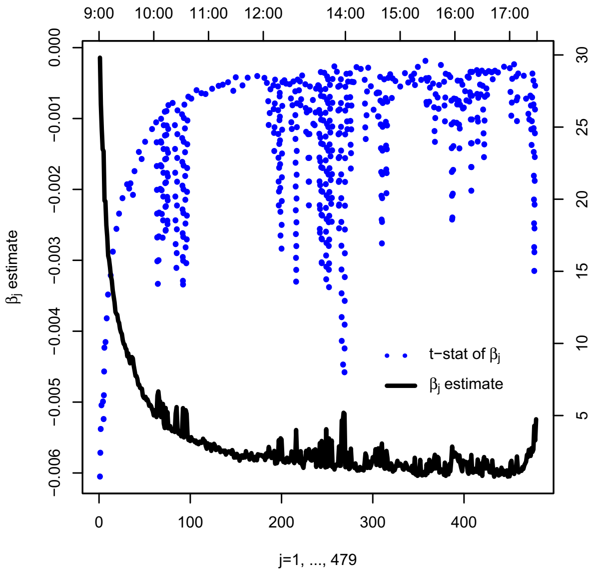

Fig. 7 This figure illustrates the estimates of β_j for large-cap stocks without the midday auction period on the left axis and respective test statistics on the right axis

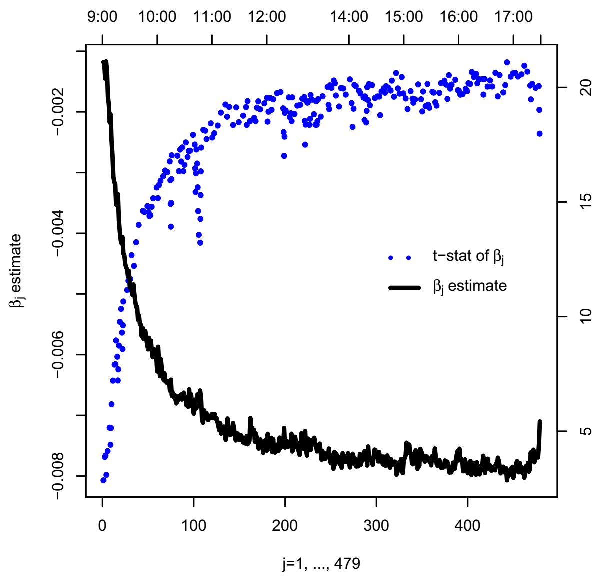

Fig. 8 This figure illustrates the estimates of β_j for small-cap stocks without the midday auction period on the left axis and respective test statistics on the right axis

Table 8 BEFORE Crisis 2002-2006 ALL STOCKS WITHOUT MIDDAY AUCTION – Estimated γ_k coefficients in Eq. (2)

	estimate	t-stat
γ_1 [Tue]	−0.00020***	−6.9115
γ_2 [Wed]	−0.00028***	−10.8904
γ_3 [Thu]	−0.00023***	−9.5783
γ_4 [Fri]	−0.00008***	−3.1318
R^2_{adj}	0.0549	
cross-sectional dimension	50	
time series dimension	105–2400	
total observations	576 302	

*** denotes statistical significance at the 1% level

Table 9 CRISIS 2007-2009 ALL STOCKS WITHOUT MIDDAY AUCTION – Estimated γ_k coefficients in Eq. (2)

	estimate	t-stat
γ_1 [Tue]	0.00003	1.4970
γ_2 [Wed]	0.00001	0.5301
γ_3 [Thu]	0.00001	0.5177
γ_4 [Fri]	0.00017***	8.5999
R^2_{adj}	0.0764	
cross-sectional dimension	252	
time series dimension	510	
total observations	586219	

*** denotes statistical significance at the 1% level

Fig. 9 This figure illustrates the estimates of β_j for all stocks from 2002-2006 without the midday auction period on the left axis and respective test statistics on the right axis

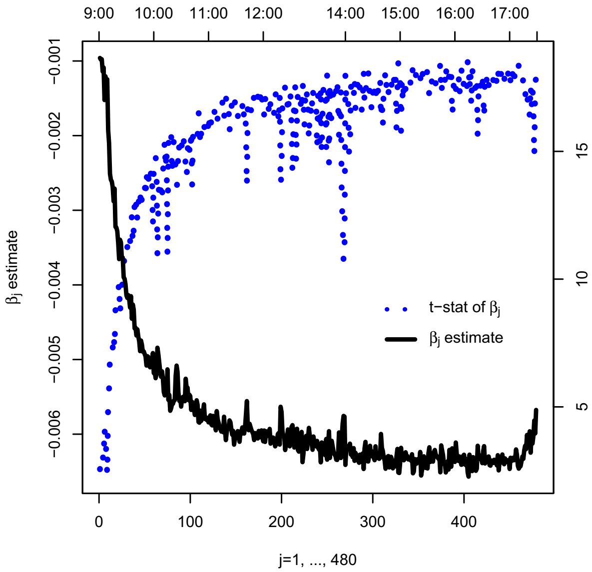

Fig. 10 This figure illustrates the estimates of β_j for all stocks from 2007-2009 without the midday auction period on the left axis and respective test statistics on the right axis

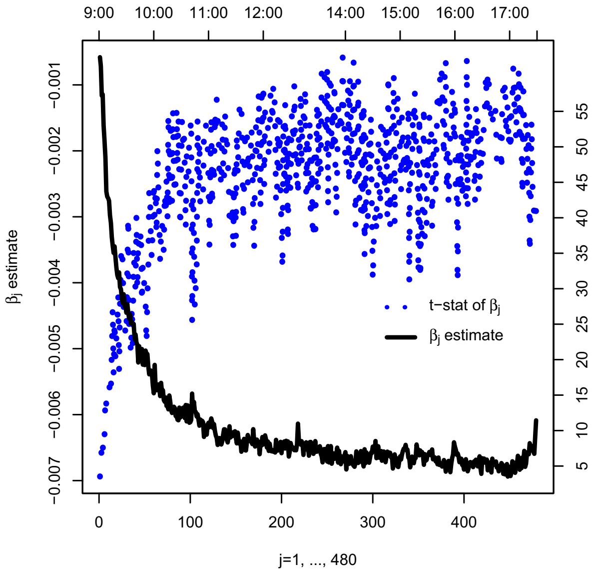

Table 10 The economic significance of intra-day spread patterns without the first 200 and the last 30 minutes. Columns I and II show the absolute savings potential. Summary statistics are provided for the absolute differences between the maximum (column I) or mean (column II) intra-day bid-ask spread and the spread during the optimal ten-minute interval. Columns III and IV show the relative savings potential. Column III provides summary statistics for the difference between the maximum and the minimum intra-day spread relative to the maximum spread, while column IV shows the respective statistics for the difference between the mean and the minimum intra-day spread relative to the mean spread

	(I)	(II)	(III)	(IV)
	Absolute savings potential		Relative savings potential	
	Max − Min	Mean − Min	$\frac{\text{Max}-\text{Min}}{\text{Max}}$	$\frac{\text{Mean}-\text{Min}}{\text{Mean}}$
Min	0.0001	0.0000	0.0484	0.0187
Max	0.0407	0.0083	0.7637	0.3983
Std. dev.	0.0028	0.0008	0.1433	0.0392
Mean	0.0014	0.0006	0.1433	0.0710
t-stat	(7.936)	(12.041)	(31.127)	(29.581)

Table 11 The number of stocks, the average market capitalisation and average bid-ask spreads for all samples

	Full S.	DAX30	L. Cap	S. Cap	02–06	07–09
# of stocks	267	37	134	133	250	252
Av. M. Cap.	3217	17 060	6231	183	2840	3777
Av. BAS	0.0072	0.0015	0.0040	0.0105	0.0079	0.0073

The analysis of small- and large-cap stocks also does not result in substantial differences in patterns.[6] Although the Friday coefficient in this analysis also becomes significant for small and large caps, it is below 1 basis point in both cases and therefore very small. Regarding intra-day patterns, no large differences are observed, except for more volatile t-statistics for large caps. (See Tables 6 and 7 and Figs. 7 and 8.)

Analysing the time frames before and during the crisis compared to the whole dataset, we observe a slight weekday pattern during the „normal times“ before the crisis and a disappearance of the weekday pattern during the crisis. We observe no substantial changes in the intra-day pattern. (See Tables 8 and 9 and Figs. 9 and 10.)

Overall, the intra-day pattern is robust in all examined choices of stocks and time frames. However, it becomes numerically very small for DAX30 stocks. The same holds for the weekday pattern, which, additionally, disappears during the crisis.

4.3 Economic Significance of Intra-day Patterns and Potential Savings

The economic significance of intra-day spread patterns is of particular interest, especially for practical purposes. To this effect, we analyse potential savings from choosing the optimal intra-day time to trade. For the sake of computability and to offer an easier to implement strategy, we changed the observation frequency of

[6] We define small and large caps by ranking all stocks by initial market capitalisation and sorting the upper 50% into the large-cap sample, with the remaining lower 50% being assigned to the small-cap sample.

our sample from one-minute to ten-minute time intervals. The first interval is from 9:00 a.m. to 9:09 a.m., the second from 9:10 a.m. to 9:19 a.m., etc., yielding a total of 51 ten-minute intervals. Whether the ten-minute interval with the lowest spread is predictable in an out-of-sample test will be addressed in Sect. 4.4.

Based on the data sample from Sect. 4.1, we aggregate, separately for each stock, the bid-ask spread for $l = 1, ..., 51$ ten-minute intervals by computing the equally weighted averages for the 51 ten-minute intervals of each weekday. By discarding the variation between weekdays, we further downsize the dataset to a panel of 267 stocks with the maximum of 51 intra-day spread observations. Next, to quantify the potential savings we compute, separately for each stock, the mean bid-ask spread and identify the ten-minute intervals with the maximum and minimum spread values.

Figure 4 depicts the cross-sectional distribution of ten-minute intra-day intervals with the lowest relative bid-ask spreads. While the distribution clearly shows considerable cross-sectional variation in the optimal time to trade, lowest spreads for most stocks occur towards the end of the trading day.

We quantify the potential savings by computing for each stock the differences between the mean or the maximum intra-day spread and the spread during the optimal ten-minute interval. Table 2 shows the summary statistics of the absolute savings potential in columns I and II and relative savings potential in columns III and IV. On average, the absolute difference between the highest and the lowest bid-ask spread equals 61 basis points. When comparing the mean intra-day spread to the minimum spread in column II, the difference still reaches 11 basis points. As column IV shows, in relative terms, this implies that the average savings potential equal 14.51% of the mean intra-day spread. In comparison to the maximum intra-day spread, on average, 52.33% of the bid-ask spread can be saved by choosing the optimal ten-minute interval to trade. Especially when taking into account that, depending on the turnover, the total savings potential is a multiple of the intra-day savings potential, we conclude that the statistically highly significant spread patterns also imply economically significant savings potential.

4.4 Out-of-sample Predictability

The savings potential from intra-day patterns being relevant and exploitable in practice depends on such patterns' predictability, which we test by a straightforward out-of-sample method. For each stock, we estimate the average bid-ask spread for 51 intra-day ten-minute intervals over the preceding 100 trading days. The interval with the lowest mean spread is used as the predicted optimal trading interval the next trading day and is denoted $\widehat{\text{Min}}$. Clearly, this prediction is based on one of the simplest conceivable approaches. As implementing substantially more elaborate methods may yield even better forecasts, the results presented below can be regarded as comparatively conservative. We require 100 trading days of input data to predict the optimal time to trade, implying that our remaining sample covers the period from

June 26, 2002 until September 30, 2009.[7] The reported results are therefore based on an unbalanced panel of 267 stocks with a maximum of 1850 daily observations each.

Analogously to the results in Table 2, we present the summary statistics of the out-of-sample approach. Panel A of Table 3 shows the absolute predicted savings in columns I and II and the relative predicted savings in columns III and IV. Accordingly, we compare the bid-ask spread during the predicted intra-day interval to the maximum spread (in columns I and III) or to the mean spread (in columns II and IV) on the same trading day. To assess the stability of intra-day patterns during the sample period and in cross-section, we present in Panel B the number of days and stocks with positive predicted savings.

The equally weighted average of the absolute difference between the spread during the predicted time interval and the interval with the maximum spread during the trading day is 68 basis points. Compared to the worst case, i.e., the maximum bid-ask spread, traders are able to save on average 61.30% of the maximum spread. The savings potential is obviously lower, although still economically significant, when comparing the spread during the predicted ten-minute interval to the mean spread of the day. The results in column II show that the equally weighted absolute deviation of the predicted spread from the mean spread is 4 basis points. While this may seem to be a comparatively small figure, it nonetheless represents 12.28% of the average spread.

The results depicted in Panel B of Table 3 indicate that the predicted savings potential is not conditional upon a sub-sample or a sub-period. We observe that on 1774 (1849) days out of 1850 days, the cross-sectional average (median) predicted savings, i.e., $\text{Mean} - \widehat{\text{Min}}$, are positive. This implies that the predicted savings are necessarily comparatively stable over time. To further exclude the possibility of our results being an artefact of a specific sub-sample of stocks, we count the number of stocks for which the predicted absolute savings potential, i.e., again $\text{Mean} - \widehat{\text{Min}}$, is positive. We observe that the time series average (median) of absolute savings is positive for 255 (264) stocks out of 267. This allows us to conclude that the savings potential we observe due to intra-day spread patterns is not driven by a specific subset of stocks.

Overall, we observe intra-day patterns to be predictable in an out-of-sample test, hence allowing us to identify practically relevant implications. Our observations have at least three normative implications. First, the comparison with the maximum bid-ask spread shows that choosing a suboptimal time to trade may result in notably higher trading costs for discretionary liquidity traders. Second, the predictability of favourable intra-day intervals is straightforward and is not conditional upon a specific sub-sample of stocks or a sub-period of data.

Finally, if discretionary liquidity traders are unable to implement any model for predicting intra-day spread patterns, the reverse J-shaped intra-day pattern implies that trading during the first 200 minutes and the final 30 minutes of a trading day

[7] To test the robustness of our out-of-sample findings, we have re-estimated all results based on a 50-day observation period to compute the optimal trading interval. As the results remain qualitatively similar, they are not reported in this manuscript but can be obtained from the authors upon request.

should be strongly avoided. Repeating the calculation of the savings potential (from Table 2) without the first 200 and the last 30 minutes, we unsurprisingly observe that potential savings decline.[8] The relative savings potential decreases by roughly 70% (in the max comparison) and by approximately 50% percent in the mean comparison analysis. We conclude that while omitting these periods is already a valid strategy, identifying the optimal window is a significantly superior one.

5 Discussion and Conclusion

Implicit trading costs have a detrimental impact on investment results. According to the study of Amihud and Mendelson (1986), only marginal investors and those with a longer holding horizon can expect to be compensated for holding illiquid stocks. Recent stock market developments, such as the introduction of electronic trading platforms or MTFs, lead to a general reduction in trading costs. However, at the same time, the stock market turnover steadily increases, causing transaction costs to be incurred increasingly more often as the average holding period is reduced. Considering the amortized spread in the sense of Chalmers and Kadlec (1998) suggests that transaction costs, such as the bid-ask spread, still impact the net returns. Therefore, strategies that allow the avoidance of unnecessarily high transaction costs by identifying intra-day periods in which bid-ask spreads tend to be low are of distinct interest to specific types of investors.

Our study' findings have normative implications, particularly for discretionary liquidity traders. The established literature on market microstructure (e.g., (Kyle 1985) or (Glosten and Milgrom 1985)) assumes that liquidity providers exploit the desire of liquidity traders for immediacy to receive compensation for losses incurred by trading with informed traders. If we consider liquidity traders, in the sense of Admati and Pfleiderer (1988), who exercise discretion as to the specific intra-day period in which to trade, our findings result in clear normative implications relevant to them. We show that, in particular, intra-day patterns in bid-ask spreads offer the possibility of reducing transaction costs and thereby increasing the net returns. To this effect, the contribution of our study is threefold.

First, the analysis of statistical significance shows a reverse J-shaped intra-day bid-ask spread pattern. In contrast, the intra-week bid-ask spread pattern was observed to be U-shaped and less pronounced than the inter-day bid-ask spread pattern. Our analyses of different subsets of stocks and time frames show that spread patterns can be assumed to be robust over time and in cross-section. Such stability of bid-ask spread patterns is the most important finding relevant in practice, i.e., to discretionary liquidity traders.

Second, to quantify the observed bid-ask spread patterns, we conduct an analysis of economic significance. The in-sample test shows that investors would have significantly reduced trading costs, by approximately 52.3%, when comparing the average minimum and maximum spreads. In addition, the average savings poten-

[8] Detailed results are provided in Table 10 of the Appendix.

tial of 14.5% between the mean spread and the ten-minute interval with the lowest spread should be economically significant as well.

Third, by conducting a simple out-of-sample test, we explore the predictability of bid-ask spread patterns and thus the possibility for discretionary liquidity traders to exploit the savings potential in practice. Presumably, the most important outcome of this test is showing that investors would have been able to consistently trade at lower spreads when predicting the optimal time to trade based on the spreads observed during the preceding 100 or 50 trading days. This finding is robust for nearly all days in the examined time series and almost all stocks in cross-section, rather than being merely a non-exploitable statistical artefact.

Nevertheless, it must be said that our results are subject to certain restrictions and simplifications owing to the approaches used. First, we assume that there is enough volume in the market and that the market is sufficiently deep, allowing traders to submit quotes at times of low spreads and, furthermore, that orders are executed without large price impacts. Such assumptions needed to be made due to the size of the dataset. However, it might be conceivable to perform such an analysis on the complete order-book data for every minute in time for all 267 stocks during all 8 years. Accordingly, a different model could consider the volume or the resilience of the market by analysing smaller datasets. However, the amount of data and processing power needed would be enormous. Having overcome the above obstacles, one could explore if the reported trading cost reductions would still be practically exploitable.

Our study points to several directions for further research. First, the assumption of the market having sufficient volume and depth is arguably very significant. An analysis of deeper levels of the order book would help us understand the validity of this assumption. Further research may complement our study and augment our findings by investigating the patterns of other implicit liquidity measures such as trading volume, price impact or market resilience. Additionally, the regression models of this study could be enhanced by including additional control variables such as risk, price, competition and firm size.

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