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Limit order books and liquidity around scheduled and non-scheduled announcements: Empirical evidence from NASDAQ Nordic

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ABSTRACT

Information arrivals may drive investors to require immediacy, generating sudden liquidity demand across multiple price levels in limit order books. We document significant intraday changes in stock limit order book characteristics and liquidity beyond the best levels around scheduled and non-scheduled company announcements. At aggregated level, liquidity beyond the best levels behaves quite differently from the bid–ask spread around scheduled announcements. Moreover, scheduled announcements improve multi-level liquidity to an exceptionally good level. We also provide evidence for pre-reactions in order books before non-scheduled announcements, which suggest the possibility of information leakage.

1. Introduction

Multi-level high-frequency data from stock order book markets has allowed researchers to empirically examine order book characteristics and dynamics (see e.g. Erenburg and Lasser, 2009; Engle et al., 2012; Deuskar and Johnson, 2011; Malo and Pennanen, 2012; Härdle et al., 2012; Gomber et al., 2015; Sensoy, 2016). As Degryse et al. (2015) argue, data beyond the best levels is intriguing, because it matters to investors as it reflects the quantity immediately available for trading and therefore the price of immediacy. It is especially important around information arrivals when informed investors may require immediacy and walk through the limit order book, taking advantage of stale limit orders, thus causing a large, immediate demand for liquidity on multiple levels.

Despite its importance, we know surprisingly little about how order book characteristics and liquidity available across multiple levels evolve around new information releases. In this paper, we aim to fill this gap with an extensive high-frequency multi-level order book data for 75 frequently traded and liquid stocks on Nasdaq Nordic markets (Helsinki, Stockholm, and Copenhagen) around first-hand stock exchange company announcements. We make the important distinction between scheduled and non-scheduled announcements, justified in Graham et al. (2006). Methodologically we follow (Malo and Pennanen, 2012; Deuskar and Johnson, 2011; Härdle et al., 2012) to capture the shape of the order book by estimating the slopes of the order book curves. The order book slopes can be used not only to characterize the order book but also to measure the order book liquidity across multiple order book levels (Malo and Pennanen, 2012). Our research question concerns how the order book characteristics and liquidity measured by order book slope across multiple levels (hereafter

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referred to as “order book liquidity”) reacts to scheduled and non-scheduled announcements, with an emphasis on comparison to the conventional spread between the best bid and ask levels.

Our research differs from the earlier studies in many important ways. In contrast to papers analysing liquidity around announcement releases with data on best levels only (see, e.g. Lee et al., 1993; Graham et al., 2006; Gross-Klussmann and Hautsch, 2011; Neuhierl et al., 2013), we use multi-level data. To our knowledge, not too many papers have employed multi-level data to study the effects of information releases on stocks' order book liquidity, but some important exceptions exist. Gomber et al. (2015) find in their study that the information content of Bloomberg ticker news is rather limited, causing no shocks to the order books, perhaps because Bloomberg is not always the first channel through which new information is distributed. We, however, document clear effects, especially with scheduled company announcements. The difference between our paper and theirs lies mainly in the type and source of the information. Additionally, Sensoy (2016) examines the impact of specific macro-announcements on liquidity commonality in Turkey. Though he addresses a different question than we do in this paper, his findings are in line with ours; order book liquidity is significantly affected beyond the best price quotes and it can be misleading to use only top-of-the-book data. Our research also relates to the study of Riordan et al. (2013), who explore the impact of Thomson Reuters newswire messages on intra-day price discovery, liquidity and trading intensity using depth at multiple price levels as one liquidity proxy. In addition to differences in methodologies and data, they do not divide the news into scheduled and non-scheduled ones. Apart from these studies, Erenburg and Lasser (2009) and Engle et al. (2012) combine multi-level data with macro announcements, but with data from the equity-index-linked securities market and the U.S. Treasury market, whereas our study focuses on equity markets with company announcements. Overall, in comparison to existing papers that use multi-level order book data, this research uses exceptionally extensive and frequently sampled data sets, examines impacts of stock exchange company announcements (instead of macro-announcements, ticker news, or newswire messages), and additionally, makes the important distinction between scheduled and non-scheduled announcements. Importantly, by these settings we provide novel results on pre- and post reactions in order books.[1]

This paper is constructed as follows. First, Section 2 introduces the order book parametrisation used in this study. Section 3 describes the data sets. Then, Section 4 demonstrates the framework of our empirical analsys, Section 5 reports the results and, finally, Section 6 summarizes and concludes the paper.

2. Order book parametrisation

An appropriate approach to characterize the order book and to measure the book's liquidity across multiple price levels should capture aspects with respect to both quantity (depth) over multiple levels and distances between the price levels. A popular approach is to estimate order book slope, which is obtained by fitting a linear curve to the order book data to measure how quantity changes as a function of price (Deuskar and Johnson, 2011; Härdle et al., 2012) or inversely, how price changes as a function of quantity (Malo and Pennanen, 2012). In this paper we technically follow (Malo and Pennanen, 2012). Importantly, the slope can be made invariant for splits and comparable between different stocks and over time, which enables an aggregated analysis.[2] In this paper, order book slope is called Order Book Illiquidity (OBI) as it measures liquidity across multiple price levels.

By interpreting buy orders as sell orders of negative quantity (see Malo and Pennanen, 2012), we can describe the state of a limit order book with marginal price curve $s(x)$, which is a piecewise constant and non-decreasing function of order quantity. We use a simple monetary measure $r(h)$, introduced by Malo and Pennanen (2012),

$$r(h) := \ln(s(h/\bar{s})) - \ln(\bar{s}),$$

where $\bar{s}$ refers to mid-price, and $h = \bar{s}x$ is the mark-to-market value of a market order of x shares—i.e. the value of the market order if we were to pay the mid-price for all the x shares. Hence, $r(h)$ gives the log change in the marginal price $s(x) = s(h/\bar{s})$ relative to the mid-price $\bar{s}$, as a function of h, the mark-to-market value of an order of x shares. Therefore, given that one buys stocks with a certain amount of money h, $r(h)$, also called the relative price impact curve, reveals how large a price impact (in monetary units) the trade has per share bought. The shape of a limit order book can be captured with a linear approximation of the relative price impact curve, which is of the form $r(h) = \text{OBI} \cdot h$. Here OBI is positive and is considered to measure order book liquidity (see Malo and Pennanen, 2012). Obviously, the smaller the value of OBI, the

[1] Siikanen et al. (2016) takes a step further and studies the factors affecting the sensitivity of order book liquidity to scheduled and non-scheduled company announcements. They also use the same datasets as we use in this study.

[2] Some other liquidity measures exist that incorporate multi-level data, too, such as the Exchange Liquidity Measure (XLM), which is based on cost of round-trip (see Gomber et al., 2015; Sensoy, 2016). However, an issue arises with XLM in our research, because it is determined for a specific trade size, yet the total multi-level depths on the bid and ask sides vary in time and consequently, the order book is not always deep enough to allow us to calculate XLM for a given order size. This is an issue especially just before announcements, when informed investors may cancel existing orders or choose not to submit new ones to avoid adverse selection, and also right after the announcements, when informed investors may take advantage of stale limit orders, both resulting in thin order book. Because the measure should be available especially around announcement times in this paper, we prefer to use order book slope as a multi-level measure—it is always possible to calculate as long as the order book is not totally empty. Additionally, Riordan et al. (2013); Engle et al. (2012)), and Erenburg and Lasser (2009) consider the depth on different price levels in the book in addition to the bid–ask spread. However, by this methodology the number of variables increases quickly when considering the depth at different levels separately, and the other dimension, distance between the price levels, is not taken into account.

more liquid the stock is. OBI is an ex-ante liquidity measure and captures information from multiple price levels in the limit order book. Whereas OBI measures the costs arising from order book illiquidity especially for large trades or a large bunch of simultaneous small trades sweeping over many price levels, spread measures the liquidity and costs of trading for small transactions that take place only at the best quotes. For visual illustration of the measure, see (Malo and Pennanen, 2012).

To eliminate the effects of the pre- and post-trading sessions, we follow Malo and Pennanen (2012) and exclude the first and last trading hours from the data. Moreover, we exclude an additional half-hour from the end of the trading day for stocks traded on OMX Helsinki and OMX Stockholm in order to get the same length of the daily periods with OMX Copenhagen. In addition, we de-seasonalise the observations of OBI, asymmetry of the two sides of the book, and relative spread. The de-seasonalisation is done by first estimating an average value for each 10-second observation moment from the estimation window for each event. We then de-seasonalise all the observations of each variable in the estimation and event windows by subtracting the average value of that moment from the observation and artificially convert them to noon, since most of the events take place around 12:00 ECT.

3. Data

3.1. Limit order book data

We use Level II order book data from NASDAQ OMX Nordic (Helsinki, Stockholm, Copenhagen), which are continuous limit order based markets.[3] Our sample includes 75 frequently traded stocks listed on NASDAQ OMX Helsinki, NASDAQ OMX Stockholm, and NASDAQ OMX Copenhagen. The stocks in our sample have been involved in the following stock indexes: OMX Helsinki 25, OMX Stockholm 30, and OMX Copenhagen 20. Out of the 75 stocks, 27 are traded in Helsinki, 28 are traded in Stockholm, and 20 are traded in Copenhagen.

We use the multi-level order book data from 1.1.2006 to 1.1.2010 and calculate the values of OBI based on snapshots of the order book taken every 10 seconds with data on the 20 best ask and bid price levels using linear regression. If there are data on less than 20 levels available, we use as many levels as possible. We distinguish the moments when trading halts occur and exclude them from this study, since normal trading and auto matching of the orders are halted during those moments. In particular, we exclude all the events from our sample for which there occurs a trading halt within the event window around the announcement release, and exclude the observations during trading halts in estimation windows when aggregating over time or events. However, the proportion of announcement releases excluded because of trading halts is relatively small. Additionally, we exclude trading days when technical errors at Nasdaq occurred and non-corrupted data was not available.

3.2. News data

The news data in this study come from NASDAQ OMX Nordic's website.[4] The announcements included in this study are from 1.1.2006 to 1.1.2010, and the respective companies filed them with NASDAQ OMX. The announcement times are given at one second precision in the data, but because we sample the order book data every 10 seconds, the times of the announcements are rounded to the nearest 10 seconds. In this paper, an announcement is considered positive (negative) if the mid-price increases (decreases) between the observation moment preceding the release and the last observation moment of the event window.

We re-categorise the announcements into two specific groups: scheduled and non-scheduled announcements. An announcement is scheduled if its exact publishing date is known to the public beforehand and non-scheduled if it is irregular, its publishing schedule is not given and cannot be reliably estimated, or the release is obviously unexpected. To be on the safe side, we exclude announcements whose publishing timespan is given non-specifically in earlier stock exchange releases or that are somewhat regular by nature.

Moreover, we exclude announcements that clearly contain no new information. These mostly include announcements published in multiple languages, in which case only the first one is involved. We also remove announcements for which we do not have enough data to form the 27-day estimation window and that have been published during non-trading hours. Additionally, if several announcements are published at the same second on the same stock, then only one of them is involved. Finally, we do not consider the cases where there has been a trading halt near the announcement time (within the pre- or post-window) ceasing continuous trading. With these restrictions we usually end up with less than 10 scheduled announcements and some dozens of non-scheduled announcements per company.

The final sample contains 329 (408) scheduled announcements and 2,102 (2,629) non-scheduled announcements with 60 (30) minute pre- and post-event windows. Just over 35% of them come from NASDAQ OMX Helsinki, around 45% orig-

[3] Data from NASDAQ Nordic has some advantages over U.S. limit order book markets. First, NASDAQ Nordic markets are little fragmented in comparison to the U.S. markets, where the limit orders for a given asset are spread between several exchanges, which poses a problem for empirical research (O'Hara and Ye, 2011), and where matching rules and transaction costs complicate comparisons between different limit order books for the same asset (Gould et al., 2013). Another advantage of using Nordic data from less liquid markets is that, as Butt and Virk (2015) argue, "it is more appropriate to test liquidity-related models in markets that are sufficiently illiquid to diagnose the level and strength of bearing [...] risks."

[4] http://www.nasdaqomxnordic.com/news/companynews , see the page also for detailed information.

inate from NASDAQ OMX Stockholm, and just under 20% are from NASDAQ OMX Copenhagen. Over 70% of the scheduled announcements in the final sample are financial announcements.

4. Framework of the empirical analysis

In our analyses, we utilise a framework from prior event studies (see, e.g. Campbell, 1997; Velásquez et al., 2016) by comparing observations in an event window around the event—in this case, announcement release—to observations in an estimation window. An estimation window comprises observations with 10-second frequency from 27 days preceding the day of an event. An event window consists of two sub-windows: a 60-minute pre-window and another 60-minute post-window. As a robustness check, we run the analyses using 30-minute pre- and post-windows and get similar results, but we report results on the 60-minute windows to demonstrate a more comprehensive data. We denote the set of observations from the estimation window (27 days preceding the announcement) by $\mathcal{E}$, from the pre-window (60 or 30 minutes preceding the announcement) by $\mathcal{A}^-$, and from the post-window by $\mathcal{A}^+$ (60 or 30 minutes following the announcement), and from the whole event window by $\mathcal{A}$ (120 or 60 minutes around the announcement).

In our aggregated analysis, to give equal weight to all the announcements and to make them comparable with each other regardless of differences in liquidity level and currency, we standardize all the values in estimation and event windows using the means and standard deviations calculated from the estimation windows.[5] In addition, to make the plots more readable and independent of number of observations N, we standardize the variables by multiplying the mean values taken over the events at each moment by $\sqrt{N}$ and consequently the variables are distributed with mean 0 and standard deviation of 1 in the estimation window.[6] We also sub-sample non-scheduled announcements from the original sample by choosing the same number of announcements as with the corresponding scheduled announcement sample with largest relative price impact (log-change in mid-price right before the event till the end of event window) to make the two event types more comparable with each other. We denote the aggregated, scaled values obtained by taking the mean over the events and multiplying it by $\sqrt{N}$ with over-line as $\overline{\text{variable}}$. Return makes an exception—in order to get an idea about the actual returns around announcements, we just apply the average values without standardization and scaling.

5. Results

5.1. Order book liquidity

To demonstrate announcement effects on the order book dynamics and the evolution of the liquidity at an aggregated level, Table 1 and Fig. 1 present $\overline{\text{OBI}}$ for the ask and bid sides of the order book separately around scheduled and non-scheduled announcement and positive and negative releases. Additionally, Fig. 1 plots the aggregated mid-price return in the event window, $\mathcal{A}$, calculated as follows:

$$r_{i,t} = \ln[m_{i,t}] - \ln[m_{i,t_0}], \quad t \in \mathcal{A},$$

where t_0 refers to the first moment in the event window $\mathcal{A}$ and $m_{i,\,t}$ denotes the mid-price for event i at time t.

Scheduled Announcements

For the scheduled announcements, the dynamics around the announcement times for all four cases (Table 1, first panel, and Fig. 1, plots A, C, E, G) are more or less the same. Notably, for the scheduled announcements, we observe that the order book liquidity during the 60-minute period before the event is much lower (i.e. OBI is higher) than in the estimation window; all the observations of $\overline{\text{OBI}}$ before the event in Table 1 are outside of the 99.9% confidence interval and in Fig. 1, $\overline{\text{OBI}}$ is constantly above the long-term maximum (obtained from the estimation window) on both ask and bid sides for positive announcements and on ask side for negative announcements. Moreover, on bid side for negative announcements $\overline{\text{OBI}}$ is well above the 95% confidence level and also reaches the long term maximum. As can be observed from Fig. 1, maximum and minimum values are sensitive to single observations and therefore it is better to analyse the results against confidence levels. We also verify the existence of statistically significant pre-reactions in the order book in all four cases by conducting a t-test comparing the mean values of OBI calculated from pre- and estimation windows (the results are available in the Online Appendix).

The results indicate that limit order books adjust to scheduled announcements before their release. The volume of limit orders standing in the book is low, indicating that many investors may have either cancelled their orders prior to the announcements or chosen not to submit new limit orders, and therefore informed investors have limited possibilities to take advantage of stale limit orders. This could indicate that investors tend not to leave limit orders standing in the order book, to avoid adverse selection.

[5] In our analysis, unit of h is 1 million EUR for stocks traded on the Helsinki Stock Exchange and 1 million SEK and 1 million DKK for stocks traded on the Stockholm and Copenhagen Stock Exchanges, respectively. While this has an impact on the values of OBI, it is not interfering our analysis since in our aggregated analysis we use standardized values.

[6] The variance of the mean taken over the events (assuming that the observations over the events are independent of each other) is $1/N$, i.e. the standard deviation is $1/\sqrt{N}$, and by multiplying the mean with $\sqrt{N}$, the scaled variable is distributed with standard deviation (and variance) of 1 in the estimation window, regardless of N.

Table 1
Order book illiquidity around announcements. This table presents observations of $\overline{OBI}$, standardised and aggregated order book illiquidity, on ask and bid sides around scheduled and non-scheduled announcements separately for positive and negative announcements. The statistical significance is calculated based on the empirical distribution of $\overline{OBI}$ from the estimation window (i.e. 27 days preceding the announcement) and indicated by asterisks: ***, **, and * indicate that the observations is outside of two sided 99.9%, 99%, and 95% confidence intervals, respectively. The non-scheduled announcement sample is extracted from the original sample by choosing the same number of announcements as with the corresponding scheduled announcement sample with largest relative price impact (log-change in mid-price right before the event till the end of event window). The sample size N is 151 for positive and 165 for negative announcements.

Scheduled announcements							
		Before					
Announcement	Variable	−10 s	−1 min	−5 min	−15 min	−30 min	−60 min
Positive	$\overline{OBI}_{Ask}$	16.59 ***	16.10 ***	14.21 ***	11.80 ***	10.83 ***	9.53 ***
	$\overline{OBI}_{Bid}$	27.52 ***	22.17 ***	17.75 ***	16.89 ***	16.29 ***	13.50 ***
Negative	$\overline{OBI}_{Ask}$	17.18 ***	17.32 ***	14.46 ***	10.45 ***	10.10 ***	8.72 ***
	$\overline{OBI}_{Bid}$	25.20 ***	25.19 ***	20.61 ***	15.75 ***	16.97 ***	9.66 ***
		After					
Announcement	Variable	+10 s	+1 min	+5 min	+15 min	+30 min	+60 min
Positive	$\overline{OBI}_{Ask}$	19.37 ***	22.89 ***	8.24 ***	0.16	−3.16 **	−4.17 ***
	$\overline{OBI}_{Bid}$	21.66 ***	23.17 ***	11.35 ***	0.62	−3.13 ***	−2.94 ***
Negative	$\overline{OBI}_{Ask}$	19.15 ***	22.83 ***	12.85 ***	2.49	−1.71	−1.68
	$\overline{OBI}_{Bid}$	28.25 ***	31.82 ***	15.05 ***	2.96	0.60	−2.20
Non-scheduled announcements							
		Before					
Announcement	Variable	−10 s	−1 min	−5 min	−15 min	−30 min	−60 min
Positive	$\overline{OBI}_{Ask}$	6.73 ***	6.49 ***	6.47 ***	6.28 ***	6.99 ***	6.46 ***
	$\overline{OBI}_{Bid}$	5.65 ***	2.66 *	6.16 ***	2.27	2.03	2.66 *
Negative	$\overline{OBI}_{Ask}$	3.05 **	3.35 **	2.99 **	4.32 ***	3.76 ***	5.01 ***
	$\overline{OBI}_{Bid}$	3.06 *	2.66 *	2.36 *	2.04	1.69	2.25
		After					
Announcement	Variable	+10 s	+1 min	+5 min	+15 min	+30 min	+60 min
Positive	$\overline{OBI}_{Ask}$	7.69 ***	9.94 ***	10.51 ***	7.34 ***	5.14 **	4.62 **
	$\overline{OBI}_{Bid}$	4.57 ***	4.78 ***	2.01	−1.50	−1.21	−1.51
Negative	$\overline{OBI}_{Ask}$	2.88 **	7.19 ***	6.56 ***	3.73 ***	3.80 ***	3.61 ***
	$\overline{OBI}_{Bid}$	5.18 ***	9.06 ***	5.32 ***	3.80 **	5.57 ***	4.68 ***

This result on the markets' pre-reaction in terms of liquidity is in line with the predictions of the traditional asymmetric information models of liquidity (see Graham et al., 2006, Table 1). Empirically, Graham et al. (2006) obtain consistent results for spread (they do not find any pattern for depth), Lee et al. (1993) with best-level-liquidity measures, and Krinsky and Lee (1996) with the adverse selection component of spread. In addition, the findings of Engle et al. (2012) on the Treasury markets and Erenburg and Lasser (2009) on the equity-index-linked securities market, both using depth at multiple price levels, show a decrease in depth before announcements, though they find that the reaction starts within five minutes before the announcements, which is in contrast to our finding that order book liquidity is at a significantly low level already an hour before an announcement release.

Next, Table 1 and Fig. 1 demonstrate that at the aggregate level, OBI starts to decline within a few minutes after a scheduled announcement and returns to a normal level within 10 to 20 minutes after the announcement, again, consistent with the predictions of the traditional asymmetric information models (Graham et al., 2006). Lee et al. (1993) find that spread and depth return to a normal level substantially slower (one day and three hours, respectively), but we argue that this is likely due to the market design and other technical developments since. The recovery time we find is consistent with the time observed in Gomber et al. (2015) using multi-level data and Degryse et al. (2005) using data on best levels to study limit order market recovery around illiquidity shocks. Our results are also in line with the findings of Engle et al. (2012) on the Treasury markets, as they find that depths at multiple levels recover fast after an announcement, and Erenburg and Lasser (2009) on the equity-index-linked securities market, as they observe that depths rise to original levels within 10 minutes after an announcement.

One of the main results of the paper is that after scheduled announcements, aggregated order book liquidity recovers to a level better than the long-term average. Particularly, for scheduled positive announcements, the level of $\overline{OBI}$ falls even below the long-term minimum, indicating that the supply of limit orders on both sides of the book is high and the transaction costs for large trades sweeping over multiple price levels are low. This may indicate that the release of scheduled announcements reduces information asymmetries and adverse selection costs significantly.

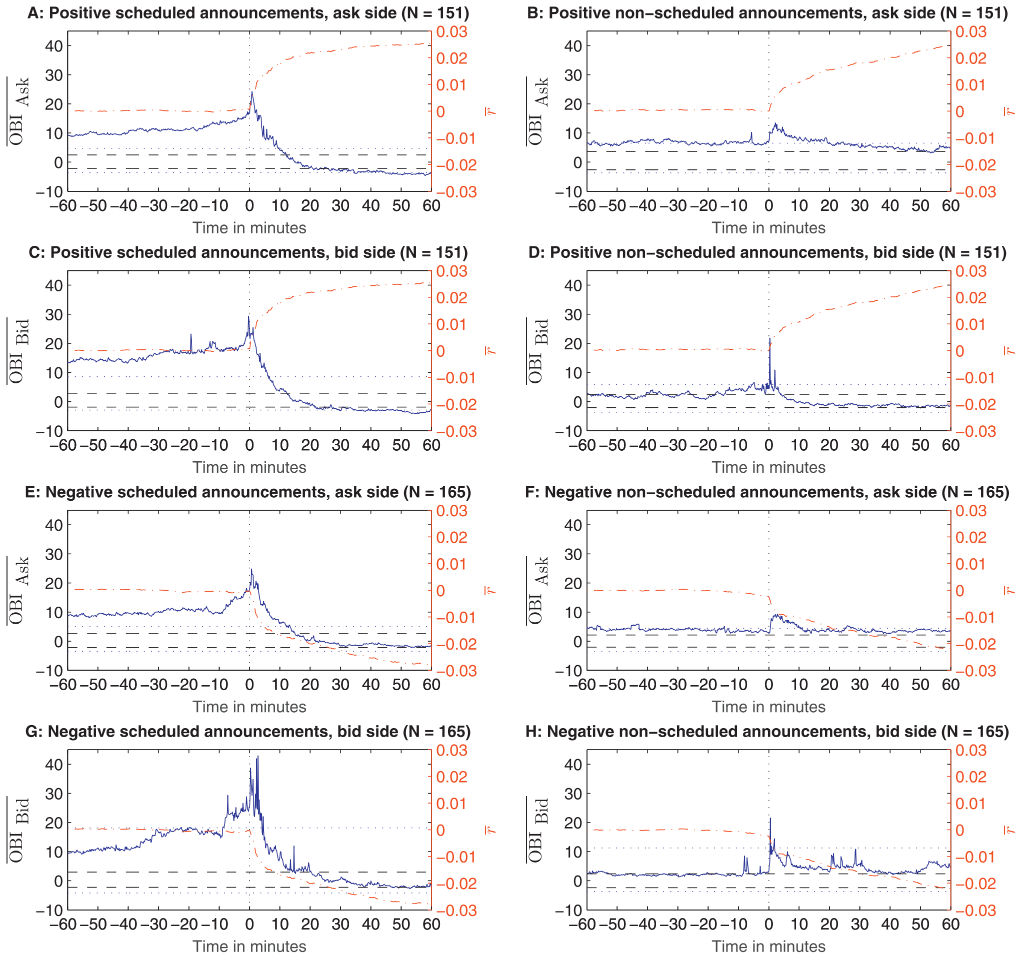

Fig. 1. Order book illiquidity around announcements. $\overline{\text{OBI}}$, standardised and aggregated order book illiquidity, on ask and bid sides around scheduled and non-scheduled announcements separately for positive and negative announcements and $\bar{r}$, average return on mid-price. The blue solid line corresponds to $\overline{\text{OBI}}$, the black dashed lines correspond to the 95% confidence level of $\overline{\text{OBI}}$ based on the empirical distribution from the estimation window (i.e. 27 days preceding the announcement) and the blue dotted lines correspond to the maximum and minimum values of $\overline{\text{OBI}}$ in the estimation window, all with the scale on the left-hand side. The red dash-dot line corresponds to $\bar{r}$ with the scale on the right-hand side in red. The black dotted vertical line at time zero corresponds to the time of the announcement. The non-scheduled announcement sample is extracted from the original sample by choosing the same number of announcements as with the corresponding scheduled announcement sample with largest relative price impact (log-change in mid-price right before the event till the end of event window). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Non-Scheduled Announcements

For non-scheduled announcements, Table 1, and Fig. 1 show statistically significant pre-reactions, especially on ask side, though the pre-reactions are clearly weaker than those for scheduled announcements. According to the predictions of traditional models, these pre-reactions can indicate information leakage (see Graham et al., 2006). In their study, Gross-Klussmann and Hautsch (2011) find an increase in spread already before the announcements.

Moreover, there is variation in the liquidity dynamics after non-scheduled announcements. On the bid side, liquidity improves to a normal level due to positive non-scheduled news (plot D), whereas the bid side liquidity remains at a relatively low level (for 60 minutes at least) after negative non-scheduled news (plot H). On the ask side, $\overline{\text{OBI}}$ peaks slightly within a few minutes after both positive and negative non-scheduled announcement releases and the order book remains relatively illiquid (plots B and F). Overall, positive non-scheduled announcements clearly improve liquidity on the bid side, but liquidity remains low in other cases (positive announcements/ask side, negative announcements/ask side, negative announcements/bid side) in comparison to its long-term mean. Riordan et al. (2013) find that liquidity increases (spread tightens and depth increases) before and after positive announcements, whereas it decreases around negative announcements (in their paper, positivity/negativity is based on the tone of the news). Graham et al. (2006) observe wider spreads and lower depth at the best levels after non-scheduled news, whereas Gross-Klussmann and Hautsch (2011) find an increased bid–ask spread around announcement releases, but find no significant effects on depth at the best levels.

5.2. Asymmetry

Next, we examine the asymmetry between the bid and ask sides, defined as

$$\mathrm{OBI}^{\mathrm{Asymmetry}} = \mathrm{OBI}_{\mathrm{Bid}} - \mathrm{OBI}_{\mathrm{Ask}}.$$

We run similar analysis on $\mathrm{OBI}^{\mathrm{Asymmetry}}$ as presented for $\overline{\mathrm{OBI}}$, and the table and the figure are available in the Online Appendix.

We find that the order book is abnormally asymmetric before scheduled announcements. In particular, ask side is relatively more liquid, meaning that it is easier to buy and harder to sell with market orders before scheduled announcements. After the scheduled announcements $\overline{\mathrm{OBI}^{\mathrm{Asymmetry}}}$ returns to normal level within 10 to 30 minutes. In contrast, asymmetry of the order book is more or less at normal levels before non-scheduled announcements. The arrival of positive non-scheduled announcements makes the book asymmetric (the ask side is relatively more illiquid) after the release, and this effect seems to be quite long lasting (at least 60 minutes). For negative announcements we observe weaker reactions, but the reaction seems to be of the opposite sign: negative non-scheduled announcements seem to make the bid side relatively illiquid.

Intuitively, when the non-scheduled news is positive, informed investors want to buy immediately using market orders that are executed against stale limit sell orders available in the book (i.e. OBI on the ask side increases). Moreover, there can exist investors who want to buy using limit orders and thus provide liquidity on the bid side (though facing uncertainty of the execution). Therefore, the imbalance between the bid and ask sides can be explained by a decrease in the provision of sell (buy) limit orders or an increase in the provision of buy (sell) limit orders, or both. The effect is exceptionally strong for positive non-scheduled events. This result implies that the news-momentum (news-contrarian) trading strategy through market orders after non-scheduled announcements is relatively expensive (inexpensive). In contrast to this, scheduled announcements decrease the transaction costs for both large buy and sell trades, keeping the book symmetric, meaning that both news-contrarian and news-momentum trading strategies are symmetrically inexpensive after scheduled company announcements.

5.3. Spread

We also compare spread (liquidity measure using best offers) and OBI (liquidity measure with multi-level data) around announcement arrivals. The relative spread—i.e. the spread between the best bid and ask divided by the mid-price (hereafter just spread)—is calculated every 10 seconds around each event (for estimation and event windows). We run similar analysis on $\overline{\mathrm{SPREAD}}$ as presented for $\overline{\mathrm{OBI}}$, and the table and the figure are available in the Online Appendix.

One should note that from the practical point of view, spread and order book liquidity measure the transaction costs for different types of trades. Around news arrivals, informed investors may require immediacy to take advantage of stale limit orders, and in this situation, it is not necessarily possible to gradually execute a large block of orders to mitigate price impact. Hence, there can be single large trades or a bunch of simultaneous smaller trades that walk up the book through many levels, increasing the practical relevance of liquidity in the book beyond the best levels and necessitating the use of multi-level data to capture the real announcement effects.

We observe a quick and strong reaction in spread around scheduled announcements: the spread starts to rise slightly above the 95% confidence level around 10 to 30 minutes before the event and peaks immediately after the announcement release, after which it starts to gradually decline, reaching normal level within around 30 to 40 minutes. This indicates that around scheduled announcements, there is a relatively short time period during which the trading cost of trades at the best levels is above the normal level.

For non-scheduled announcements, $\overline{\mathrm{SPREAD}}$ is slightly above the normal level already before releases especially for negative announcements. After the non-scheduled announcements release, $\overline{\mathrm{SPREAD}}$ peaks to well above the long-term maximum value (obtained from the estimation window). Aggregated spread seems to stay above the long-term level during the whole 60 minute post event window.

Importantly, the observed effect of scheduled announcements on order books with data on multiple price levels is significantly different from what the spread between the best prices indicates. Whereas (i) $\overline{\mathrm{SPREAD}}$ rises significantly just 10 to 30 minutes before a scheduled announcement and (ii) new information does not improve it beyond its long-term level, $\overline{\mathrm{OBI}}$ (i) rises to an abnormally high level well (at least 60 minutes) before the scheduled news arrives and (ii) improves even beyond its one-month minimum in 20–30 minutes. Given that the order book slope reflects differences in investors views on the stock price and hence is related to information asymmetry, multi-level order book data provide evidence that scheduled news releases (especially positive ones) *reduce* the information asymmetry in stock markets in comparison to the long-term level, which cannot observed from the best levels.

6. Summary and conclusion

This paper examines the stock limit order book characteristics and liquidity around scheduled and non-scheduled company announcements using high frequency multi-level limit order book data of 75 frequently traded stocks listed on exchanges belonging to NASDAQ Nordic for the years 2006 to 2009. Parameterising the order book data with an order book slope enables us to measure the liquidity available over multiple price levels of the order books.

In the aggregated analysis, we find quite contradictory results for the multi-level order book liquidity measure (order book slope) and conventional bid–ask spread: whereas multi-level order book liquidity is exceptionally low at least an hour before the release of a scheduled announcement, the spread widens significantly only 10–30 minutes before the announcement comes. Additionally, unlike the spread, the multi-level liquidity measure improves to an exceptionally good level, even beyond its one-month record after the release of a scheduled announcement, which may indicate that scheduled announcements reduce information asymmetry. Hence, our results provide evidence that order book liquidity is significantly affected beyond the best price quotes and it can be misleading to use only top-of-the-book data, which is in line with the findings of Sensoy (2016). Additionally, we find that before the release of *non-scheduled* announcements, aggregated order book liquidity is above the normal level with statistical significance (especially on the ask side), which can indicate information leakage (see Graham et al., 2006).

We also find that the asymmetry of the order book is at an abnormally high level after the release of a non-scheduled announcement so that the ask (bid) side is abnormally illiquid in comparison to the bid (ask) side after positive (negative) news. This indicates that a news-momentum (news-contrarian) trading strategy is relatively expensive (cheap) after the release of non-scheduled announcements. Interestingly, scheduled announcements do not demonstrate such a phenomenon; they improve the liquidity on both sides of the order book equally.

There are some limitations in our study. Most importantly, we use multi-level data, but not order flow data (ITCH feed), which would be the most comprehensive data on order book markets. In future research, it would be interesting to use order flow data to study how order book liquidity is provided and consumed around announcements. For example, does the liquidity decrease due to trades (executions) or order cancellations? The statistical properties of message arrivals (submissions, cancellations, executions) around news releases would shed more light on the liquidity provision in the limit order markets around information releases.

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Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.frl.2016.12.016

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