Stock liquidity in forefront of anticipated announcements

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Abstract

The paper studies the effects of anticipated earnings announcements on liquidity before the earnings announcement day, utilizing full limit order book data. We find very convincing supportive evidence of deteriorating liquidity due to the increase in information asymmetry, which is in line with existing literature. We contribute to the literature showing that supply and demand elasticities, and hence overall market depth, are much stronger adversely affected, as best bid and best ask quotes would suggest.

Keywords: *liquidity measures, earnings announcements, supply curve elasticity, limit order book*

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1 Introduction

Theoretical market microstructure models like Kyle (1985) predict deteriorating liquidity when fundamental uncertainty about the true stock price rises. It is widely accepted that uncertainty about next day fundamental stock value is substantially higher for pre-earnings announcement days than for other days. Empirically Kyle's prediction with respect to earnings announcements has been supported (Lee et. al 1993, etc.), however mostly for tightness measures, such as bid-ask spreads, which capture transaction costs for minimal trades. Whereby Kyle's prediction mainly concerns another dimension of liquidity – price impact or market depth, capturing price movement, caused by larger transactions. We close this gap in the literature explicitly studying the impact of increasing fundamental uncertainty on the elasticity of supply and demand for stocks utilizing full order book data. In fact, we obtain results supportive of much stronger impact of uncertainty on supply and demand slopes than on the usually studied bid-ask spreads.

Earnings announcements present an exceptionally attractive opportunity to study the effect of information asymmetry on liquidity because of the two things: their timing is usually known beforehand, and they contain market-moving information. Thus, if the market-maker expects an increase in probability of dealing with an insider trader in times before earnings announcements, it is logical to assume that liquidity should shrink. Any possibility of information leakage before the earnings announcement leads to elevated in- formation asymmetry. However, even if there is no leakage, information asymmetry risk may increase before earnings releases for two reasons. First, the market-maker bears the risk that other traders may obtain and trade on the public news before she gets a chance to resubmit her quotes. Although the market-maker's information may be as recent as others', in this day and age of widespread high-frequency algorithmic trading, her commitment to provide tradable quotes opens her to potential losses if any trader has even a few milliseconds advantage. Another risk is that the expectation of upcoming earnings releases may prompt some traders to look for information immediately prior to the announcement. In both instances, the market-maker is at a bigger risk in periods before announcements.

Lee et al. [24] provide findings that bid-ask spreads are increased and depths at best bid and best ask quotes are decreased during trading hours before earnings announcements compared to non-event periods. Investors suffer from this plunge, because market liquidity is one of the most crucial characteristics that investors seek in an organized financial market. Market liquidity relates to the ability to buy or sell significant quantities of a security quickly, anonymously, and with relatively little price impact [21]. Low market liquidity decreases the demand for shares and the share price.

Because of this reduced share price, attracting equity capital for companies becomes more costly. Therefore, it is important to explore the drop in market liquidity around earnings announcements. In theory, a liquid market implies that any trades are executed instantly and with no price impact. Practically, however, if there is uncertainty with respect to asset values, market liquidity could decrease significantly. Earnings announcements usually bear this uncertainty. Empirical research rarely attempts to incorporate the fact that theoretical predictions concerning liquidity behavior depend on whether the timing of an event is known in advance. With that in mind, we examine market conditions before anticipated[1] earnings announcements to try and answer the following questions: how do anticipated earnings announcements affect market liquidity? Does this effect resonate through all levels of the order book?

We investigate 100 NYSE-listed companies over a three-year period from 2010 to 2012 using event-study methodology. A distinguishing trait of our study is the usage of tick limit order book data, which allows us both to reconstruct complete order book for any stock at any given time and to look at liquidity measures that go beyond best bid and best ask quotes, while also providing us with huge number of data points, therefore making the study more precise and the findings more accurate. We also place the focus of the empirical research on the day before the announcement day to see how far-reaching the effect of earnings announcements on order book is.

Overall, our results are consistent with models that predict a drop in liquidity before anticipated events due to increased informational asymmetry (e.g. Glosten-Milgrom [14], Kyle [19], Copeland and Galai [7], Kim and Verrecchia [17]). We find that information asymmetry increases during the day prior to earnings announcement and that it affects order book on all levels, resulting in reduced depth and increased dispersion of orders. Our results yield a stronger impact of uncertainty on deeper levels of order book compared to best quotes.

In section 2 we go through theoretical and empirical works that deal with different aspects of liquidity around market events, then we describe data sources and characteristics in section 3 before turning to methodology of our research and empirical results in section 4. The results of this paper are summarized in section 5.

[1] By anticipated we mean that the date and the timing of announcement are known by market participants in advance. Note that announcements may bear surprise content regardless of whether the timing of the event is known or not.

2 Literature Review

In this section we summarize papers that deal with liquidity behavior around anticipated company-specific events. We start with fundamental theoretical works and move to empirical research afterwards.

The most insightful theoretical works on the topic naturally lie in the field of market microstructure and have been revolving mainly around asymmetric information models, which traditionally predict that information asymmetry increases prior to a news announcement and gradually decreases afterwards. Most of these models involve informed and uninformed (liquidity, noise) traders. Uninformed traders know only the timing of the upcoming announcement, but informed on top of that also possess private information regarding the contents of the announcement. Naturally, informed traders are in a privileged position to capitalize on their superior knowledge. In a situation that involves information-heavy event like earnings announcement, uninformed traders are reluctant to trade as it is likely that informed traders have valuable private knowledge. Consequently, market makers reduce liquidity because the probability of trading with informed traders increases in such situations. Thus, liquidity is expected to be abnormally low in periods preceding these events (Glosten and Milgrom [14], Kyle [19]).

Another model that leads to similar predictions, although through a slightly different mechanism, is the Kim-Verrecchia model [17]. Instead of assuming that informed traders are endowed with private information, Kim and Verrecchia suggest that all traders have the same access to information and actively gather it prior to earnings announcements, although informed are in a better position to succeed in their searches, to process that information and come to correct conclusions (in a context of this model, one can think of informed traders as professional equity analysts). Numerous extensions of aforementioned models exist, but most of them end up with the same results regarding the information asymmetry effect on liquidity.

A number of empirical articles deal with information processing around company- specific events. There's a certain degree of controversy in the literature regarding the effects of earnings announcements on liquidity. Brooks [2] investigates spreads around earnings and dividends announcements and concludes that spreads and spread components change significantly around earnings releases, indicating the informativeness of such events. However, he finds that this isn't true for dividends announcements. Lee, Mucklow and Ready [24] also investigate earnings announcements of NYSE-listed companies and state that market makers increase spreads and reduce depth prior to announcements, probably to offset the losses from trades with insiders who dominate the market just before the announcement.

Morse and Ushman [23] found no effect of information announcements on the quoted bid-ask spread. Venkatesh and Chiang [22] find sizeable changes only in case when no other announcement is released in the 30 days before the earnings announcements. Ranaldo [27] looks into liquidity provision driven by firm-specific news at the Paris Bourse and finds that only news that cause large price disruptions (e.g. earnings announcements) increase information asymmetry risk and decrease liquidity.

Pronk [26] investigates the impact of intraday timing of earnings releases on the dip in liquidity around these releases and the importance of richness of information environment before these announcements. He concludes that liquidity is less sensitive to announcements when they happen during non-trading hours and questions whether the drop in liquidity before news releases is caused by market-makers' preparations to such events. Lakhal [20] looks into liquidity and stock prices components of information asymmetry around earnings announcements, concentrating on effective spreads and trading volumes. His results indicate that overall announcements boost liquidity in the event window, but also increase asymmetry right before and after announcements. Johnson and So [15] link changes in liquidity prior to announcements with earnings announcement premia. They show, both theoretically and empirically, that market makers asymmetrically increase transaction costs they demand for stacking sell orders relative to 8 buy orders prior to announcements, implying that they would rather sell existing inventory ahead of earnings news, thereby reducing risks.

Furfine [13] examines the variability of price impact of a trade throughout the days surrounding earnings announcements. He indicates that public releases correspond to a reduction in price impacts, which, he says, is consistent with announcements weighing over asymmetric information component of stock trading. However, he finds that this effect does not typically go beyond the announcement day.

3 Data

We get limit order book data from NYSE TAQ OpenBook database. In the first part of our empirical study we examine a sample of 100 NYSE-listed companies during the years of 2010-2012 (in the second part – a 42 stock subsample in 2011). Companies were chosen almost randomly, with a slight preference towards more liquid ones.

We use Bloomberg to obtain earnings announcements dates and whether these announcements were anticipated or not. Since we don't have information on the exact timing of earnings announcements, we focus on the day before the day of announcement as reported by Bloomberg. We require a stock price of at least 3 dollars and a minimum of at least 100 quotes on the day previous to the event day. After applying this filter, we have 92 companies left out of initial 100 with total number of event days of 1,087. Non-event estimation period includes all trading days for 92 companies for three years from 2010 to 2012 excluding an interval of [-2:+2] trading days around the event date. We take intraday tick data for each firm in a corridor from 9:40AM to 3:50PM for each day to avoid frequent errors in the data during the first and the last several minutes of trading (standard NYSE trading hours are from 9:30AM to 4:00PM). Thus, we have c.370 observations of each liquidity measure per stock per day (some observations were deleted due to errors in the original data). Total number of observation points for event days is 381,243 and for non-event days is over 21mn. Sample selection process is presented in the table below.

Table 1: Sample selection

Initial number of companies	100
Stock price below	$3 (3)
Less than 100 quotes on previous day	(5)
Remaining number of companies	92
Total event days for all companies	1,087
Total event observation points	381,243
Total non-event days for all companies	61,243
Total non-event observation points	21,544,726

NYSE TAQ OpenBook database provides date, timestamp, reference price (price of the last book sale), type of the order (bid/ask), order price, and change in size of the order (which could be both positive and negative). One of the biggest challenges was to find a way to conveniently process this information as no existing packages for R (or any other statistical software for that matter) can work with raw NYSE OpenBook data. Because NYSE doesn't provide id for each order change, one is not able to say which order was altered exactly and why (was it an addition of a new order, a trade, a cancellation or a removal), and therefore is forced to treat all orders for the same price and direction as one. We leave out reference price (as this research doesn't take into account trades per se) and implement the following procedure to compute liquidity measures.

We process the data for each company and each day separately. We take a subset of the datatable for the first minute available (which is 00:00 – orders left from the previous close) and divide it into a table for bids and a table for asks. we then collapse both tables by price (sum sizes of all orders of the same price and direction) so that there's only one order left for each price point. After that, all orders of size zero are deleted, leaving just relevant bids and asks, their corresponding prices and sizes (i.e. complete order book) at the end of the minute, which is all that's necessary to compute the liquidity measures. For the next minute, the same mechanism is implemented, only new orders are now added to already existing bids and asks tables, which then are again collapsed. This is repeated for each minute until the market is closed. All observations outside of the interval from 9:40 to 3:50 are then deleted. We find this to be a very convenient algorithm to process the data with its imperfections, and it solves the problem of the data being irregularly spaced over time. We ran this algorithm in R statistical software to obtain one full order book snapshot for each minute in the admissible range.

4 Methodology and Empirical Research

In this section, we present the empirical analysis of market liquidity before anticipated earnings announcements.

Firstly, taking a larger sample we provide convincing evidence that deep-in-the-book liquidity is affected by the announcement-driven rise in information asymmetry. Secondly, on a smaller sample we explore in detail which levels and which sides of the limit order book are mostly prone to the rise in uncertainty.

For the first part we consider several simple measures that take into account orders beyond best bid and best ask:

Dispersion of the orders:

$$DisDt_j = \frac{1}{2}\left(\frac{\sum_{i=1}^{n} w_i^{Buy}(Bid_{i-1} - Bid_i)}{\sum_{i=1}^{n} w_i^{Buy}} + \frac{\sum_{i=1}^{n} w_i^{Sell}(Ask_i - Ask_{i-1})}{\sum_{i=1}^{n} w_i^{Sell}} \right) \quad (1)$$

$$DisSp_j = \frac{1}{2}\left(\frac{\sum_{i=1}^{n} w_i^{Buy}(Midquote - Bid_i)}{\sum_{i=1}^{n} w_i^{Buy}} + \frac{\sum_{i=1}^{n} w_i^{Sell}(Ask_i - Midquote)}{\sum_{i=1}^{n} w_i^{Sell}} \right) \quad (2)$$

The weights w_i are the total sizes at the i-th bid and ask quotes, normalized by dividing each weight by the sum of all weights. When $i = 1$, the measure considers the interval between the mid-quote and the best quotes. The first equation measures the distance between the orders of two consecutive quotes, while the second measures the distance between each order and the mid-quote. The more disperse the orders are in the book, the higher the dispersion measure and the lower the liquidity in the book.

Naive depth:

$$NDepth_j = \frac{1}{2}\left(\frac{\sum_{i=1}^{n} w_i Q_i^{Buy}}{\sum_{i=1}^{n} w_i} + \frac{\sum_{i=1}^{n} w_i Q_i^{Sell}}{\sum_{i=1}^{n} w_i} \right) \quad (3)$$

Naive depth measures the weighted average depth of the book by taking into account both the number of shares and corresponding price levels. Higher weights are assigned to orders placed closer to the best quotes. Its name comes from the fact that it neither considers the distance between the orders in the book nor takes into account the volume of trading activities typical for a particular stock. Nevertheless, naive depth is computed in this paper as an additional convenient liquidity measure of the order book.

These indicators are calculated at the end of each minute during NYSE trading hours for the best 5 quotes on both bid and ask sides.

To construct normal (non-announcement) dispersion measures and naive depth, we run mean adjusted return model. This model assumes that the measures are constant over time for the estimation period but differ from stock to stock.

$$E[DisDt_{jt}] = ConstDisDt_j$$
$$E[DisSp_{jt}] = ConstDisSp_j$$
$$E[NDepth_{jt}] = NDepth_j$$

All of the measures are expressed as a percentage deviation from non-event average for the same firm. These standardized measures allow for comparisons across firms with their normal values. All calculations are conducted on a firm-by-firm basis and then aggregated to get mean values. We compare the cross-sectional mean of the measures during the event period with a corresponding measure generated during the non-announcement period. Null hypothesis is that earnings announcements have no impact on the behavior of liquidity (event and non-event means are equal), or:

$$H_0 : \mu_{non-event} = \mu_{event}$$

$$H_1 : \mu_{non-event} \neq \mu_{event}$$

We implement *t*-statistic and Wilcoxon-Mann-Whitney test to check if the differences between announcement and non-announcement periods are significant. Tests results for *t*-statistic are summarized in the table below.

Table 2: Percentage deviations in the event period

	DisDt	DisSp	NaiveDepth
Total event observation points (N = 381,243)			
Expected sign	+	+	-
Percentage deviation from mean	4.32	6.65	-8.42
Results are significant at 1% level	√	√	√

Wilcoxon-Mann-Whitney test also shows that all percentage deviations are significant at 1% level. Thus, the null hypothesis is rejected and a conclusion follows that earnings announcements have a statistically significant negative impact on liquidity the day before the announcement.
As a robustness check, we also take two additional approaches to non-event period. First, instead of taking all days during the three years to form one non-event period, we take 75 days prior to each event and compare cross-sectional mean of each event with the mean of the corresponding non-event period. Thus, we have 12 events for each firm during the three years, and 12 non-event periods. The results of this approach are largely the same. Second, we take a random sample from initial non-event period of the size similar to event-period one, and test the null hypothesis one more time. Again, the approach yields similar results. These findings are consistent with previous theoretical and empirical research. Moreover, they show that liquidity drop before the announcements affects all levels of order book by both decreasing its depth and increasing price levels distance. Evidence shows that order book during the day before the day of earnings announcements becomes less deep and more disperse. Dispersion measures (DisDt and DisSp) increase by 4.32% and 6.65%, respectively, and naive depth decreases by 8.42%. Those numbers are higher in absolute values than changes in liquidity measures based on the best bid and ask quotes obtained in research papers discussed in section 2, which means that deeper levels of order book are generally more affected than higher levels.

In the second part, to manifest the findings of the first part and gain further insights, we take a deeper look into the orderbook for a sub-sample of 42 stocks in 2011. We consider wider liquidity measures: elasticities of demand and supply curves of the limit order book, as well as an average elasticity of both curves. Since elasticity varies along the curve, we take averages across considered price levels similar to the approach of Naes and Skjeltrop (2006), e.g. average supply elasticity for each 1-minute snapshot $s \in [1,\ldots,381]$ is calculated as:[2]

$$SE_{it}^{s} = \frac{1}{N}\sum_{\pi=1}^{N}\frac{\left(V_{\pi+1}^{A}-V_{\pi}^{A}\right)/V_{\pi}^{A}}{\left(P_{\pi+1}^{A}-P_{\pi}^{A}\right)/P_{\pi}^{A}}\,, \quad (4)$$

where π indicates a price level (number from midpoint, i.e. best ask has an index π=1), N-the number of considered price levels, V_{π}^{A} is accumulated volume of all (ask) orders to sell at π or lower, P_{π}^{A} denotes quoted ask price on the π^{th} price level. The formula for the demand elasticity DE_{it}^{s} is

[2] In contrast to Naes and Skjeltrop (2006) we refrain from including the part of the slope from midpoint to the best ask, as it involves measurement in a different scale.

calculated analogically. We calculate average daily elasticity for each side of the book, SE_{it} and DE_{it}, as well as an overall average daily elasticity AE_{it}

$$SE_{it} = \frac{1}{381}\sum_{s=1}^{381} SE_{it}^{s}$$

$$AE_{it} = \frac{SE_{it} + DE_{it}}{2}$$

We calculate these elasticity measures for 10 best quotes (i. e. N=10), further referred to as *Ask 10 Elasticity*, *Bid 10 Elasticity* and *Av. 10 Elasticity*, as well as for the whole curve (N=N_{max}), referred to as *Ask Total Elasticity*, *Bid Total Elasticity* and *Av. Total Elasticity*.

For comparison purposes we also consider a standard narrow liquidity measure *Quoted spread*:

$$Quoted\ Spread_{it}^{s} = \frac{BestAsk - BestBid}{\left(BestAsk + BestBid\right)/2} \quad (5)$$

Table 3. Descriptive statistics

	Quoted spread	Av. Total elasticity	Av. 10 elasticity	Bid total elasticity	Ask total elasticity	Bid 10 elasticity	Ask 10 elasticity
Mean	5.83	487.04	3253.75	-406.75	567.00	-2993.38	3489.21
Median	4.64	487.19	3324.39	-416.08	547.37	-3086.57	3517.14
Maximum	57.64	1769.26	22740.60	-15.42	3004.56	-51.06	39600.39
Minimum	0.37	15.16	50.56	-1289.42	14.89	-9583.70	50.06
Std. Dev.	5.14	242.55	1515.99	212.86	297.48	1272.16	1803.60
Observations	10366	10405	10419	10423	10403	10414	10403

Quoted spread is multiplied by 10000, so that it is reported in basis points.

Table 3 gives a brief overview of the data properties. We consider quite liquid stocks, with an average quoted spread of merely 6 basis points. Elasticity at closest to midpoint 10 price levels is 6-7 times higher than the total elasticity. Supply elasticity seems to be slightly higher than the demand side, which is in contrast to Kalay et al. (2004).

Table 4. Correlations

	Quoted spread	Av. Total elasticity	Av. 10 elasticity	Bid total elasticity	Ask total elasticity	Bid 10 elasticity	Ask 10 elasticity
Quoted spread	1.00	-0.18	-0.43	0.12	-0.21	0.45	-0.39
Av. Total elasticity	-0.18	1.00	0.55	-0.93	0.97	-0.53	0.52
Av. 10 elasticity	-0.43	0.55	1.00	-0.37	0.62	-0.95	0.97
Bid total elasticity	0.12	-0.93	-0.37	1.00	-0.80	0.42	-0.32
Ask total elasticity	-0.21	0.97	0.62	-0.80	1.00	-0.57	0.62
Bid 10 elasticity	0.45	-0.53	-0.95	0.42	-0.57	1.00	-0.85
Ask 10 elasticity	-0.39	0.52	0.97	-0.32	0.62	-0.85	1.00

From Table 4 one can see that all liquidity measures are related. However, the tightness measure has correlations below 0.5 with all the elasticity measures, indicating that those convey also to a substantial extent some other information about stock liquidity. Therefore studying explicitly properties of supply and demand curves becomes more valuable.

To test for the effect of an anticipated announcement on a liquidity measure LM_{it} , $LM \in$ { *Ask 10 Elasticity*, *Bid 10 Elasticity*, *Av. 10 Elasticity*, *Ask Total Elasticity*, *Bid Total Elasticity*, *Av. Total Elasticity*, *Quoted Spread*}, we specify a regression for each stock liquidity measure. Our variable of interest is a dummy for pre-announcement days, $PreEAD_{it}$. We control for persistence of liquidity measures including first- and second-order autoregressive terms. Furthermore, around August 1, 2011 some event seemed to lead to deteriorating liquidity across the market. We control for it introducing a dummy variable $August_t$. Thus, the expression for each stock becomes:

$$LM_{it} = \alpha_i + \gamma_i \cdot August_t + \delta_i \cdot PreEAD_{it} + \beta_{1i} \cdot LM_{it-1} + \beta_{2i} \cdot LM_{it-2} + \varepsilon_{it} \text{ , (6)}$$

We estimate equation (6) for a liquidity measure for all 42 stocks simultaneously applying the Seemingly Unrelated Regressions approach. Subsequently we test whether the pre-announcement day uncertainty had a liquidity deteriorating effect:

$$\sum_{i=1}^{42} \delta_i = 0$$

The predicted sign depends on the measure: worsening liquidity widens *Quoted Spread* (+) and adversely effects elasticity: "-" for *Ask 10 Elasticity*, *Av. 10 Elasticity*, *Ask Total Elasticity*, *Av. Total Elasticity* and "+" for *Bid 10 Elasticity* and *Bid Total Elasticity*, since demand curve is downsloping.

Table 5. Effect of the pre-announcement day on liquidity measures

	Quoted spread	Av. Total elasticity	Av. 10 elasticity	Bid total elasticity	Ask total elasticity	Bid 10 elasticity	Ask 10 elasticity
EA-effect	0.22	-29.2	-435.9	30.2	-37.2	430.0	-462.1
χ^2-stat	14.0***	39.5***	79.0***	79.3***	22.2***	337.0***	48.2***

First line reports an average effect of a pre-announcement day on a liquidity measure, obtained from a SUR system of equations of type eq. 6, $\frac{1}{42}\sum_{i=1}^{42}\delta_i$. Liquidity measures are defined in Eq. 4-5. Second line reports Wald test-statistic for the null-hypothesis $\sum_{i=1}^{42}\delta_i = 0$, it is chi-squared distributed with one degree of freedom.

Table5 presents the result of our empirical test. We can see that our prediction is supported for all measures. Thereby the deteriorating effect of an anticipated earnings announcement is highly statistically significant (p-value<0.001 for all liquidity measures and for some p-value<0.0001). Statistical significance is stronger for depth measures than for the quoted spread. Moreover, statistically (but not economically) the result is stronger for the demand curve elasticity than for the supply elasticity. Economically the effect on elasticity is at least three times stronger than on spreads: on the pre-announcement day spreads rise by 4% of their standard deviation, whereas *Av. Total Elasticity* drops by 12% of standard deviation (see Table 3, Table 5); the effect is even more pronounced for the range of best 10 ticks: *Av. 10 Elasticity* worsens by 28% of its standard deviation. Moreover, in this range demand elasticity deteriorates substantially stronger than the supply elasticity: one third vs. one fourth standard deviation.

Thus, we find strong support of a more pronounced impact of earnings uncertainty on market depth than on market tightness of the stock. Thereby we find that the elasticity of demand deteriorates stronger relatively to its variation.

5 Conclusion

The paper studies the effects of anticipated earnings announcements on liquidity before the earnings announcement day. We find very convincing supportive evidence of deteriorating liquidity due to the fundamental uncertainty, which is in line with existing literature. Our contribution is that we show that market depth is much stronger adversely affected, as best bid and ask quotes would suggest. Moreover, demand elasticity suffers more in relative terms from unresolved firm-specific uncertainty than supply elasticity.

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