What drives the sensitivity of limit order books to company announcement arrivals?

What drives the sensitivity of limit order books to company announcement arrivals?[☆]

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Abstract

We provide evidence that recent losses amplify order book illiquidity shocks caused by non-scheduled news. Moreover, the faster markets' reaction to scheduled and non-scheduled news arrivals is in terms of order book illiquidity, the more illiquid the order book becomes; that is, a fast reaction is a strong reaction. Additionally, order book asymmetry observed before announcement arrivals is positively associated with the magnitude of illiquidity shocks.

Keywords: Limit order book; Liquidity; Company announcement; High-frequency data
JEL classification: G10, G14

1. Introduction

Many studies show that information arrivals can cause liquidity shocks (see e.g. Erenburg and Lasser, 2009; Engle et al., 2012; Riordan et al., 2013; Rosa, 2016; Siikanen et al., 2017). However, to our knowledge there are no earlier studies investigating the factors which affect the magnitude of liquidity shocks in limit order books (LOB) caused by announcement releases. In this paper, we aim to explain the sensitivity of LOB liquidity to information arrivals using high-frequency LOB data for 75 companies from NASDAQ Nordic combined with set of scheduled and non-scheduled company announcements, for four-year period of 2006–2009.

LOB characteristics and the liquidity dynamics beyond the best levels are intriguing, especially around information arrivals, because high trading activity and investors' impatience may generate a sudden liquidity demand across multiple price levels. Thus, using the conventional bid–ask spread might lead to misleading results (Rosa, 2016; Sensoy, 2016; Siikanen et al., 2017). An appropriate method to characterize the LOB and to measure the LOB 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 (see e.g. Deuskar and Johnson, 2011; Härdle et al., 2012; Malo and Pennanen, 2012; Siikanen et al., 2017), which in this paper is called Order Book Illiquidity (OBI).[2]

Siikanen et al. (2017) find that after the immediate illiquidity shock, scheduled announcements can improve LOB liquidity to exceptionally good level and provide evidence for pre-reaction in

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[2] Some other liquidity measures exist that incorporate data from multiple LOB levels, too, such as the Exchange Liquidity Measure (XLM). However, an issue arises with XLM, because this measure 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 LOB is not always deep enough to allow us to calculate XLM for a given order size. This is an issue especially just before scheduled announcements.

LOBs before scheduled announcements, which suggests the possibility of information leakage (see also Graham et al., 2006).[3] Additionally, Riordan et al. (2013) and Gomber et al. (2015) study liquidity over multiple LOB levels in equity markets around information arrivals. Apart from these studies, Erenburg and Lasser (2009), Engle et al. (2012), and Rosa (2016) combine multi-level LOB data with macro announcements, but with data from equity-index-linked securities market, the U.S. Treasury market, and futures market, respectively. However, none of these studies looks extensively into the factors driving the LOB sensitivity, which is the focus of this paper.

We use 20 order book levels to calculate OBI, and one should note that this may affect the results presented here. Specifically, Siikanen et al. (2017) show that spread behaves quite differently around announcement releases when compared to OBI, so it is also likely that OBI calculated for example over 5 or 10 levels behaves differently from OBI over 20 levels. Additionally, we restrict our analysis to liquid stocks, and the results for illiquid stocks may differ considerably.[4]

2. LOB Parametrisation and liquidity measure

To parametrise the LOB, we follow Malo and Pennanen (2012). The shape of a LOB is linearly captured as follows:

$$r(h) = \mathrm{OBI} \cdot h,$$

where

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

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. Here OBI is positive and is considered to measure LOB liquidity (see Malo and Pennanen, 2012).[5] Obviously, the smaller the value of OBI, the more liquid the stock is.

We use simple linear regression to calculate the values of OBI based on snapshots of the LOB taken every 10 seconds including data from 20 best ask and bid price levels. In case there are not 20 different price levels available on one side of the book, we use as many as are available. We also eliminate the effects of the pre- and post-trading sessions and exclude the first and last trading hours from the data.[6] In addition, we de-seasonalise the observations of ln(OBI).

3. Data

We use LOB data from 1.1.2006 to 1.1.2010 for 75 frequently traded stocks listed on NASDAQ OMX Helsinki, Stockholm, and Copenhagen, which are continuous limit order based markets. The stocks in our sample have been involved at some point in OMX Helsinki 25, OMX Stockholm 30, or OMX Copenhagen 20. Out of the 75 stocks, 27 are traded in Helsinki, 28 are traded in Stockholm, and 20 are traded in Copenhagen.[7]

The news data in this study come from NASDAQ OMX Nordic's website.[8] The announcement times are given at one second precision in the data, but because we sample the LOB data every 10 seconds, the times of the announcements are rounded to the nearest 10 seconds. We do not restrict our study to any specific news class, such as earnings announcements, as many other studies do.

[3] Siikanen et al. (2017) use largely the same data sets as we use in this study.

[4] We thank an anonymous referee for pointing out these important observations.

[5] Malo and Pennanen (2012) refer to LOB illiquidity as β, but for clarity, we refer to it as OBI, since in the finance literature β usually refers to CAPM β.

[6] For stocks traded on OMX Helsinki and OMX Stockholm, we remove an additional half-hour from the end of the trading day because of the different length of the trading day in comparison to OMX Copenhagen.

[7] We use data from Nordic markets instead of U.S. markets (the most liquid in the world) because the former are little fragmented in comparison to the latter. In the United States, fragmentation is clearly an important feature of equity markets (O'Hara and Ye, 2011). 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."

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

Rather, we re-categorise the announcements into two specific groups: scheduled and non-scheduled announcements (see Siikanen et al., 2017, for the categorization). The final sample contains 408 scheduled and 2,629 non-scheduled announcements: 35%, 45%, and 20% originate from NASDAQ OMX Helsinki, Stockholm, Copenhagen, respectively. Over 70% of the scheduled announcements in the final sample are financial announcements.

4. Empirical Analysis

4.1. Framework of the Empirical Analysis

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 30-minute pre-window and another 30-minute post-window. We denote the set of observation times from the estimation window by $\mathcal{E}$, from the pre-window by $\mathcal{A}^-$, and from the post-window by $\mathcal{A}^+$, and from the whole event window by $\mathcal{A}$.

4.2. Regression Variables

The dependent variable measures the relative magnitude of LOB illiquidity shock due to the release of information:

$$\Delta \ln(\mathrm{OBI})^{\mathrm{Max}}_{\mathcal{E},\mathcal{A}+} = \max_{t \in \mathcal{A}^+} [\ln(\mathrm{OBI})_t] - \ln(\mathrm{OBI})^{\mathrm{Med}}_{\mathcal{E}},$$

where

$$\ln(\mathrm{OBI})^{\mathrm{Med}}_{\mathcal{E}} = \underset{t \in \mathcal{E}}{\mathrm{Median}}[\ln(\mathrm{OBI})_t],$$

is a median observation from the estimation window.

We choose the explanatory variables to capture pre-reactions in the LOB, the sign (positiveness/negativeness) of new information, and the markets' reaction times. The first explanatory variable, $\ln(\mathrm{OBI})^{\mathrm{Med}}_{\mathcal{E}}$, is used to control for the preceding level of ln(OBI) (for the ask and bid sides separately).

Second, the expectations of the effects of the announcements may be visible in the pre-announcement window, which can indicate information leakage (see e.g. Lee, 1992; Graham et al., 2006; Siikanen et al., 2017). Intuitively, if the liquidity available on the ask side is exceptionally low in comparison to the bid side, it might be that the markets are expecting a positive announcement and vice versa. So, our second explanatory variable is the maximum asymmetry, calculated as

$$\ln(\mathrm{OBI})^{\mathrm{Asymmetry}}_{\mathcal{A}-} = \max_{t \in \mathcal{A}^-} \left[\left| \ln(\mathrm{OBI})^{\mathrm{Bid}}_t - \ln(\mathrm{OBI})^{\mathrm{Ask}}_t \right| \right].$$

To assess the effects of price pre-reactions to illiquidity shock, the third explanatory variable is

$$r_{\mathcal{E},\mathcal{A}-} = \ln \left[\underset{t \in \mathcal{A}^-}{\mathrm{Median}}(m_t) \right] - \ln \left[\underset{s \in \mathcal{E}}{\mathrm{Median}}(m_s) \right],$$

where m_t denotes the mid-price at time t.

The fourth explanatory variable is the median relative spread in the pre-window, denoted by $\mathrm{SPREAD}^{\mathrm{Med}}_{\mathcal{A}-}$. Here we use observations from the pre-event window to avoid a correlation with the other liquidity measure, $\ln(\mathrm{OBI})^{\mathrm{Med}}_{\mathcal{E}}$.

The fifth explanatory variable in the regression is time in minutes from the release of an announcement to the maximum value of ln(OBI) within the post-window. Formally, by setting $\min[\mathcal{A}^+] = 0$,

$$\tau^* = \underset{t \in \mathcal{A}^+}{\mathrm{argmax}} [\ln(\mathrm{OBI})_t].$$

With this variable, we investigate how the length of "reaction time" from a release to an illiquidity shock is associated with the magnitude of the shock. One can also think of this variable from the

Table 1: **Association between LOB illiquidity shock and LOB related factors.** The robust standard errors appear in parentheses. Economic significance levels are reported in braces and they give the change in the maximum relative price impact due to announcements: for α_1 – α_4 they are based on one standard deviation increase in explanatory variables and for α_5 on 10 minutes increase in τ^* (α_6 is an estimate of a dummy variable).

		Scheduled announcements		Non-scheduled announcements	
Parameter	Variable	ask	bid	ask	bid
α_1	$\ln(\mathrm{OBI})^{\mathrm{Med}}_{\mathcal{E}}$	-0.098* (0.046) {-0.184}	-0.229** (0.073) {-0.373}	-0.065** (0.021) {-0.123}	-0.046 (0.024)
α_2	$\ln(\mathrm{OBI})^{\mathrm{Asymmetry}}_{\mathcal{A}-}$	0.121 (0.074)	0.445*** (0.107) {0.284}	0.072* (0.028) {0.041}	0.291*** (0.045) {0.178}
α_3	$r_{\mathcal{E},\mathcal{A}-}$	-0.339 (0.543)	-0.407 (0.534)	-1.655*** (0.260) {-0.142}	-1.121*** (0.266) {-0.099}
α_4	$\mathrm{SPREAD}^{\mathrm{Med}}_{\mathcal{A}-}$	70.176*** (10.788) {0.188}	61.635*** (12.983) {0.163}	29.972*** (3.421) {0.086}	12.117 (9.610)
α_5	τ^*	-0.017*** (0.005) {-0.171}	-0.023** (0.008) {-0.228}	-0.005*** (0.001) {-0.051}	-0.003* (0.001) {-0.032}
α_6	D_+	0.150* (0.075)	-0.261* (0.107)	0.146*** (0.032)	-0.122*** (0.029)
Number of observations		408	408	2,629	2,629
R^2		0.081	0.166	0.098	0.095

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

perspective of aggressiveness: is there an association between how fast (i.e. aggressively) liquidity is consumed and what is the amount of liquidity consumed?

The last explanatory variable in our regression is a dummy variable for positive events, D_+, which is 1 if the news is positive—that is, the mid-price at the end of the post-window is larger than the mid-price right before the announcement. Importantly, we calculate τ^* and D_+ from post-window whereas other variables are calculated from pre-window. Means, medians, and standard deviations of the regression variables are available in the Online Appendix.

Overall, our stock-specific fixed effect regression is of the form:[9]

$$\begin{aligned}\Delta\ln(\mathrm{OBI})^{\mathrm{Max}}_{\mathcal{E},\mathcal{A}+} = \alpha_1 \cdot \ln(\mathrm{OBI})^{\mathrm{Med}}_{\mathcal{E}} + \alpha_2 \cdot \ln(\mathrm{OBI})^{\mathrm{Asymmetry}}_{\mathcal{A}-} + \alpha_3 \cdot r_{\mathcal{E},\mathcal{A}-} \\ + \alpha_4 \cdot \mathrm{SPREAD}^{\mathrm{Med}}_{\mathcal{A}-} + \alpha_5 \cdot \tau^* + \alpha_6 \cdot D_+. \end{aligned} \tag{1}$$

4.3. Regression Results

Table 1 presents the regression results. The estimated regression coefficients for $\ln(\mathrm{OBI})^{\mathrm{Med}}_{\mathcal{E}}$ indicate that the more liquid the stock, the larger the illiquidity shock due to the announcement with

[9]Alternatively, Equation 1 can be expressed as

$$\begin{aligned}\max_{t\in\mathcal{A}+}[\mathrm{OBI}_t] = (1+\alpha_1)\cdot \mathrm{OBI}^{\mathrm{Med}}_{\mathcal{E}} + \alpha_2 \cdot \mathrm{OBI}^{\mathrm{Asymmetry}}_{\mathcal{A}-} + \alpha_3 \cdot r_{\mathcal{E},\mathcal{A}-} \\ + \alpha_4 \cdot \mathrm{SPREAD}^{\mathrm{Med}}_{\mathcal{A}-} + \alpha_5 \cdot \tau^* + \alpha_6 \cdot D_+.\end{aligned}$$

both statistical and economic significance.

For $\ln(\mathrm{OBI})_{\mathcal{A}-}^{\mathrm{Asymmetry}}$, the estimated regression coefficients indicate that the larger the imbalance between the ask and bid sides before the event, the larger the maximum illiquidity cost after the announcement. The asymmetry seems not only be statistically but also economically significant, especially with the bid side illiquidity shock. This result supports the result of Chordia et al. (2002) that order imbalances in either direction reduce liquidity.

The estimates of $r_{\mathcal{E},\mathcal{A}-}$ for non-scheduled announcements suggest with statistical and economic significance that the more the stock price decreases (increases) before the announcement arrival, the larger (smaller) the impact of the announcement is on the magnitude of illiquidity. This finding seems consistent with the study of Hameed et al. (2010), who document that negative market returns decrease liquidity.[10] It is interesting that there is no apparent statistical association with scheduled announcements. Overall, this result can be used to understand investor reactions to unexpected news releases: recent losses can make investors' liquidity provision more sensitive to announcements whose arrival is unexpected.

The regression coefficients estimated for $\mathrm{SPREAD}_{\mathcal{A}-}^{\mathrm{Med}}$ indicate with statistical and economic significance that the larger the relative spread before the announcement, the larger the illiquidity shock the announcement causes. Interestingly, this is contradictory with respect to other liquidity measure, $\ln(\mathrm{OBI})_{\mathcal{E}}^{\mathrm{Med}}$. However, they are calculated from different windows, which can partially explain the difference. Also, as demonstrated in Siikanen et al. (2017), multi-level liquidity and spread can behave differently around announcement releases (see also Sensoy, 2016; Rosa, 2016).

For τ^*, the estimated regression coefficient show that the faster the illiquidity shock occurs after the announcement, i.e. the faster the LOB illiquidity reaches its maximum after a news release, the larger the illiquidity shock is. As the table demonstrates, if the shock occurs 10 minutes later, its magnitude decreases by approximately 17–23% for scheduled announcements and 3–5% for non-scheduled announcements.

The parameter estimates for dummy variable D_+ show that, in comparison to negative news releases, positive news releases cause larger illiquidity shocks on the ask side and smaller shocks on the bid side and vice versa. This is reasonable because informed investors may buy (sell) shares by picking off stale sell (buy) limit orders just after the arrival of new positive (negative) information.

As a robustness check, we run the regressions using 60-minute pre- and post-event windows, and get similar results (the results are available in the Online Appendix). As an additional robustness check, we run the regressions using mean values instead of median values and the results are essentially the same as those reported for the median values and are available upon request.

5. Summary and Conclusion

We perform regression analysis to explain the magnitude of the illiquidity shock that follows scheduled and non-scheduled company announcement releases, and find several associations with both statistical and economic significance. Most importantly, recent losses make the illiquidity shock following a non-scheduled announcement larger. Moreover, a fast reaction is a strong reaction; that is, the faster the LOB illiquidity reaches its maximum after a news release, the more illiquid the LOB becomes. We also provide evidence that the LOB asymmetry before both scheduled and non-scheduled announcements is positively associated with the magnitude of illiquidity shocks.

The results may be sensitive to the number of LOB levels used to determine multi-level liquidity, and future research should consider using different numbers of levels to see how this affects the findings. Additional analysis with different liquidity measures and on less liquid stocks could also provide new valuable insights on the topic. In the future research, it would also be interesting to use order flow

[10] We perform an additional analysis to check if squared returns between the estimation window and illiquidity shocks at the post-event window, $r^2_{\mathcal{E},\mathcal{A}+}$, are associated with realised returns, $r_{\mathcal{E},\mathcal{A}-}$, but find no statistically significant associations (see Online Appendix).

data to study how different factors affect directly the order submission and cancellation rates (liquidity provision) around company announcements.

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Appendix A. Means, medians and standard deviations of regression variables

Table 2 presents the means, medians, and standard deviations of the variables in our regression. We can see that the size of the relative illiquidity shock after scheduled announcement releases ($\Delta \ln(\mathrm{OBI})^{\mathrm{Max}}_{\mathcal{E},\mathcal{A}+}$) is, on average, larger than the one after nonscheduled announcements.[11] The average liquidity on bid side is lower than on the ask side ($\ln(\mathrm{OBI})^{\mathrm{Med}}_{\mathcal{E}}$ is higher), which is consistent with the observation of Malo and Pennanen (2012). The illiquidity peak takes place most commonly around 3 minutes after the scheduled announcement releases. For non-scheduled announcement releases, the peak happens usually around 13 (25) minutes after the announcement when we use the sample with 30 (60) minute pre- and post event windows. The maximum asymmetry of the book ($\ln(\mathrm{OBI})^{\mathrm{Asymmetry}}_{\mathcal{A}-}$) seems to be slightly larger before scheduled announcement releases, whereas relative spread remains the same. The average price change from the estimation window to the pre-event window ($r_{\mathcal{E},\mathcal{A}-}$)is positive for scheduled and negative for non-scheduled announcement releases in our sample. Moreover, scheduled announcement sample includes relatively more announcements with positive price impact after the release than the non-scheduled announcement sample.

[11] See also Siikanen et al. (2017) for illustrations on evolution of OBI around scheduled and non-scheduled announcements.

Table 2: **Descriptive statistics of the regression variables.** Means, medians, and standard deviations of the regression variables. Side indicates for which side of the LOB, bid or ask side the variable is calculated. Some of the variables, such as mid-price returns are common for both sides.

Scheduled

Side	Variable	30 min Mean	30 min Median	30 min StDev	60 min Mean	60 min Median	60 min StDev
Ask							
	$\Delta\ln(\mathrm{OBI})^{\mathrm{Max}}_{\mathcal{E}_i,\mathcal{A}+}$	0.889	0.892	0.813	0.981	0.940	0.746
	$\ln(\mathrm{OBI})^{\mathrm{Med}}_{\mathcal{E}}$	-4.926	-4.796	2.082	-5.049	-5.028	2.094
	τ^*	6.696	2.833	8.275	11.431	2.833	17.474
Bid							
	$\Delta\ln(\mathrm{OBI})^{\mathrm{Max}}_{\mathcal{E}_i,\mathcal{A}+}$	1.094	1.028	0.976	1.190	1.122	0.929
	$\ln(\mathrm{OBI})^{\mathrm{Med}}_{\mathcal{E}}$	-4.810	-4.632	2.045	-4.931	-4.906	2.067
	τ^*	7.429	3.333	8.570	11.932	3.500	16.919
common							
	$\ln(\mathrm{OBI})^{\mathrm{Asymmetry}}_{\mathcal{A}-}$	1.110	1.034	0.561	1.248	1.103	0.582
	$r_{\mathcal{E},\mathcal{A}-}$	0.014	0.019	0.083	0.015	0.020	0.079
	$\mathrm{spread}^{\mathrm{Med}}_{\mathcal{A}-}$	0.002	0.002	0.002	0.002	0.002	0.002
	D_+	0.507	1.000	0.501	0.459	0.000	0.499
Number of observations			408			329	

Non-Scheduled

Side	Variable	30 min Mean	30 min Median	30 min StDev	60 min Mean	60 min Median	60 min StDev
Ask							
	$\Delta\ln(\mathrm{OBI})^{\mathrm{Max}}_{\mathcal{E}_i,\mathcal{A}+}$	0.340	0.289	0.627	0.417	0.363	0.625
	$\ln(\mathrm{OBI})^{\mathrm{Med}}_{\mathcal{E}}$	-5.323	-5.429	2.033	-5.267	-5.376	2.043
	τ^*	13.210	11.833	10.019	26.591	24.667	20.219
Bid							
	$\Delta\ln(\mathrm{OBI})^{\mathrm{Max}}_{\mathcal{E}_i,\mathcal{A}+}$	0.355	0.324	0.659	0.452	0.411	0.664
	$\ln(\mathrm{OBI})^{\mathrm{Med}}_{\mathcal{E}}$	-5.205	-5.335	2.036	-5.148	-5.288	2.048
	τ^*	13.587	12.667	9.933	26.791	24.500	20.083
common							
	$\ln(\mathrm{OBI})^{\mathrm{Asymmetry}}_{\mathcal{A}-}$	0.961	0.840	0.565	1.080	0.948	0.578
	$r_{\mathcal{E},\mathcal{A}-}$	-0.009	0.003	0.093	-0.008	0.002	0.092
	$\mathrm{spread}^{\mathrm{Med}}_{\mathcal{A}-}$	0.002	0.002	0.003	0.002	0.002	0.003
	D_+	0.436	0.000	0.496	0.447	0.000	0.497
Number of observations			2,629			2,102	

Appendix B. Regression results with 60-minute event windows

Table 2 presents the regression results using 60 minute pre-and post event windows.

Table 3: **Association between LOB illiquidity shock and LOB related factors using 60 minute pre- and post event windows.** The robust standard errors appear in parentheses. The regression results using the 30- and 60-minute pre- and post-event windows are mostly consistent, though some small variation exists. A potential reason for this is that an increase in the length of the window decreases the sample size, as some news releases occur too close to the beginning or end of the trading day to form the pre- and post-event windows. The use of the 60-minute window leads to around 20% decrease in the sample size when compared to the 30-minute window.

		Scheduled announcements		Non-scheduled announcements	
Parameter	Variable	ask	bid	ask	bid
α_1	$\ln(\text{OBI})_{\mathcal{E}}^{\text{Med}}$	-0.080	-0.180*	-0.036	-0.036
		(0.049)	(0.082)	(0.022)	(0.027)
α_2	$\ln(\text{OBI})_{\mathcal{A}-}^{\text{Asymmetry}}$	0.199**	0.422***	0.087**	0.270***
		(0.073)	(0.121)	(0.031)	(0.054)
α_3	$r_{\mathcal{E},\mathcal{A}-}$	-0.012	0.006	-1.736***	-1.040***
		(0.597)	(0.575)	(0.337)	(0.297)
α_4	$\text{SPREAD}_{\mathcal{A}-}^{\text{Med}}$	86.849**	73.779**	26.331***	21.096*
		(30.803)	(22.181)	(7.767)	(10.412)
α_5	τ^*	-0.006*	-0.009***	-0.002**	-0.001
		(0.002)	(0.003)	(0.001)	(0.001)
α_6	D_+	0.146	-0.263*	0.144***	-0.142***
		(0.075)	(0.106)	(0.034)	(0.040)
Number of observations		329	329	2,102	2,102
R^2		0.100	0.166	0.100	0.090

*** p < 0.001; ** p < 0.01; * p < 0.05

Appendix C. Squared Return Regression

We run a linear regression to explain the squared returns from the estimation window to the illiquidity shock for non-scheduled announcements. In particular, the dependent variable is

$$r^2_{\mathcal{E},\mathcal{A}+} = \left(\ln\left[m^{\text{max, ln(OBI)}}\right] - \ln\left[\underset{t\in\mathcal{E}}{\text{Median}}(m_t)\right]\right)^2,$$

where $m^{\text{max, ln(OBI)}}$ is the mid-price at the moment when ln(OBI) reaches its maximum value in the post-event window. Note that $r^2_{\mathcal{E},\mathcal{A}+}$ is *not* the log return to the maximum mid-price in the post event window, but for the moment, ln(OBI) reaches its maximum value after the event. For a robustness check, we also use the squared periodic return instead of log return, i.e.

$$r^2_{\mathcal{E},\mathcal{A}+} = \left(\frac{m^{\text{max, ln(OBI)}}}{\text{Median}_{t\in\mathcal{E}}(m_t)} - 1\right)^2,$$

An explanatory variable is $r_{\mathcal{E},\mathcal{A}-}$. We run the regression separately for the ask and bid sides (the maximum ln(OBI) can be reached at different times for the ask and bid sides), 30- and 60-minute event windows, and both log-return and periodic return versions of $r^2_{\mathcal{E},\mathcal{A}+}$ for non-scheduled announcements. We use the within-transformation as in the regressions of the original paper.

Only one out of eight regressions gives a statistically significant regression estimate (bid side, 30-minute window, log-return version: $\hat{\alpha} = 0.234^*$ (robust standard error = 0.119)), while the rest of the regression estimates are insignificant and are not provided here, but are available upon request.