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Escape from the Market: Discretionary Liquidity Trading

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Abstract

Using two types of corporate events, a scheduled announcement and an unscheduled announcement, I investigate the effect of information asymmetry on trading volume. Only before a scheduled announcement, such as an earnings announcement, can I observe decreasing trading volume. I construct a simple theoretical model that suggests how ex ante information asymmetry and discretionary liquidity trading could cause the decreasing trading volume only before a scheduled announcement. Finally, analyzing the relationship between this decreasing trading volume and proxies of ex ante information asymmetry, such as analyst coverage, size, and industry categorization, I test and confirm an information asymmetry hypothesis about the trading volume pattern before a scheduled announcement.

(Keywords: timing information, information asymmetry, trading volume)

1. Introduction

When there is an information issuance in the future, informed investors may have two types of informational advantage over uninformed liquidity investors. One advantage is provided by information about future cash flows and the other is by timing

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information of this corporate event. For example, the CEO of IBM knows a target company that IBM will acquire and knows the timing of this announcement. In this case, no one except for informed investors can infer these two kinds of information. However, there is another type of an announcement, such as an earnings announcement, whose timing can be anticipated by even uninformed liquidity investors. Even though liquidity traders do not know the magnitude of the cash-flow information from the announcement, they know there will be a considerable piece of information on a specific day, and this knowledge is common to everyone in the market. Since liquidity traders lack only the information about cash flow, they can optimize their trading with the timing information, as argued in Admati and Pfleiderer(1988) or Foster and Viswanathan(1990). If higher price sensitivity or more informed investors in the market are expected, discretionary liquidity investors will not participate in trading because of the adverse selection cost. Also, another important participant, the market maker who sets the price and maintains its continuity, knows the timing and rationally expects the existence of strategically behaving liquidity traders. Therefore, the market maker should consider the less amount of liquidity trading originated from the behavior of discretionary liquidity traders.

On the other hand, in the case of an unscheduled announcement, the market participants other than informed traders cannot determine when this announcement will be issued. The discretionary liquidity traders cannot adjust their behavior prior to the announcement, and informed traders will have more opportunity to trade strategically. Also, the market maker cannot rationalize the existence of strategically behaving discretionary liquidity traders. The difference between the inferences drawn by the market maker under the two different circumstances, combined with the existence of discretionary liquidity traders, raises interesting questions about trading volume in equilibrium.

Among many scheduled and unscheduled announcements, this paper deals with earnings announcements and takeover announcements. I select these two data sets because of the ease of use; and in addition these two major corporate events have been widely studied and their impact on return and trading volume is considered to be substantial.[1)]

For documentation about an anticipated information event, Abraham and Taylor(1997), Kim and Verrecchia(1991a), Ederington and Lee(1993), and Li and Engle(1998) etc. can be cited. However, these researchers seldom investigate the trading volume before an anticipated announcement and never relate it to ex ante information asymmetry. For example, Ederington and Lee(1993) examine the impact of scheduled macroeconomic announcements, such as the employment report, the consumer price index, and the producer price index, on interest rate and foreign exchange futures markets. They mostly concentrate on analyses on volatilies in these markets and do not investigate trading volume.

Many studies in financial economics and accounting have developed theoretical models and performed empirical tests about trading volume. We can roughly categorize those documents into four different groups.

First, there are summary and/or descriptive papers as presented by Karpoff(1987). Similarly, Lo and Wang(2000) provide a systematic description of trading volume data.

Second, the relationship between volatility and trading volume has been theoretically and empirically studied. For example, the hypothesis established by Kyle(1985) or Admati and Pfleiderer (1988) that private information revealed through trading causes variance is tested by Barclay et al.(1990).[2)]

Third, there is an effort to interpret trading volume as an explanatory variable for the cross-sectional variation of expected return. Lee and Swaminathan(2000) show that trading volume can indicate the phase of the return process in which a stock is positioned between the periods favorable for the momentum strategy and for the value strategy. As a liquidity measure, Chordia et al.(2001) use the second moment of trading volume and show that there is a negative cross-sectional relationship between this measure and stock returns.[3)]

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1) See Foster, Olsen and Shevlin(1984), Jensen and Ruback(1983), and Jarrell and Poulsen(1989).

2) For this category, see Gallant, Rossi, and Tauchen(1992), Shalen(1993), Jones, Kaul and Lipson(1994) etc.

3) As related papers, there are Gervais et al.(2000), Lo and Wang(2001), etc. Even though some of these papers have a considerably different intuition, all

Finally, with regard to market microstructure, numerous studies have been implemented about the relationship among information asymmetry, trading volume, and stock returns. For example, Kyle(1985), Bamber(1987), Admati and Pfleiderer (1988), Atiase and Bamber(1994), Wang(1994), He and Wang (1995), Foster and Viswanathan(1990), Kim and Verrecchia (1991a, 1991b, and 1994) are included in this category. Bamber(1987) tries to link the size of trading volume on an earnings announcement day with the significance of news. Atiase and Bamber(1994) follow the hypothesis of Bamber(1987) and empirically show that there is a positive relationship between the trading volume on an earnings announcement day and information asymmetry measured by the analyst coverage. However, they do not consider how the discretionary liquidity trader's behavior is related to the trading volume process before an announcement. Although Kim and Verrecchia(1994) analyze the effect on trading volume from an earnings announcement, they concentrate mostly on ex post information asymmetry which, according to their hypothesis, results from investors' different abilities in interpreting the announced information. This paper, which can be included in the fourth category, introduces a typical trading volume pattern caused by ex ante information asymmetry.

Admati and Pfleiderer(1988) theoretically explain the empirical observation of a U-shaped intraday trading volume through the argument that discretionary liquidity traders and informed traders will concentrate their trading in the period when the price sensitivity from the order flow is the least in the market maker's pricing function. Also, Foster and Viswanathan(1990) extend the result of Admati and Pfleiderer(1988) in a continuous time model and argue that discretionary liquidity trading is worthwhile only with a public announcement. However, in these models, they did not consider the inference problem of the market maker.

If discretionary traders trade strategically, the market maker should rationally expect the level of participating discretionary liquidity traders. After considering the existence of discretionary

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of them try to use trading volume to explain the cross-sectional variation of stock returns.

liquidity traders in the market maker's pricing procedure,[4] the present analysis predicts that the total expected trading volume will be smaller. Actually, the trading volume will be eventually at the same level as that in the case of no ex ante discretionary liquidity traders in the market. Therefore, even though there exist ex ante discretionary liquidity traders in the market, once market participants recognize the existence of these discretionary liquidity traders, all of the discretionary liquidity traders will in equilibrium escape from the market and the expected trading volume will be smaller.

In this paper, I not only describe an interesting pattern of trading volume prior to a scheduled announcement, but also relate this pattern with ex ante information asymmetry by applying the results from the present model. If a discretionary liquidity trader does not recognize much difference between an informed trader and herself, her cost from deferring trade is much larger than the expected adverse selection cost, and she will not escape from the market. Therefore, she continues to trade and we will not observe the decreased trading volume in this case. Since the size, the number of analysts, and industry characteristic of a company can be considered to be a measure of ex ante information asymmetry before earnings announcements,[5] I use these variables to show the effect of information asymmetry on trading volume prior to an announcement. If the size of a company is smaller, fewer analysts cover a company, or a company is in an industry where informed investors have more advantage than uninformed traders before an earnings announcement, I observe that the trading volume before a scheduled announcement is less.

This paper is organized as follows. In section 2, I describe the trading volume pattern before different types of announcements. In section 3, I suggest a simple model that includes the market maker's different pricing function with respect to the scheduledness of an announcement. With this model, I can explain the empirical findings in section 2. Section 4 contains cross-sectional empirical investigations and robustness checks.

4) This is an added value of this paper to Kyle(1985) or Admati and Pfleiderer (1988).

5) For example, see Hong et al.(1998) or Atiase and Bamber(1994).

Finally, in section 5, I offer concluding remarks.

2. Empirical findings

a. Data and description of variables

As a scheduled announcement, I select an earnings announcement. The empirical studies about the return and trading volume near earnings announcements are well documented in many previous works such as Bamber(1987), Bamber and Cheon(1995) or Foster, Olsen, and Shevlin(1984). As shown in these studies, we can observe considerable dynamics in return and trading volume near earnings announcements. Among other corporate announcements, a takeover announcement would have as much effect on the return and trading volume as an earnings announcement. Also, such announcements are not scheduled, so I select takeover announcements to exemplify unscheduled announcements.

For the earnings announcement sample, the I/B/E/S earnings announcement data from 1986 to 1997 are used. From the I/B/E/S summary files, analysts' forecasts of earnings per share(EPS), reported EPS, and reporting dates are extracted. The total number of earnings announcements during this period is 43,321 all from NYSE and AMEX companies.

The information about acquiring and target companies in NYSE or AMEX is collected from the SDC database. In order to match the period, the data only between 1986 and 1997 are included. Sometimes, the announcement dates are estimated in the database, but in this analysis, only actual announcement dates are used. The total number of acquiring companies is 16,854 and that of targeted companies 11,235.

CRSP daily data for all companies in NYSE or AMEX from 1986 to 1997 are combined for these two samples in order to obtain trading volume.

To control firm-specific characteristics and increase the power of my tests, I matched the companies between the earnings data and the takeover data in the robustness check section. By matching, the companies in the earnings data will have at least one takeover announcement, and the companies in the takeover

Table 1. Data sets and applied filters

NYSE and AMEX	Earnings[a]	Acquisition[b]	Target[c]
Before # of Obs. Filter	43,321	16,854	11,235
After # of Obs. Filter	41,697	15,134	8,448
After Matching with Acquisition	34,942	11,024	N/A
After Matching with Target	30,618	N/A	4,877

a. The earnings announcement data between 1986 and 1997 are extracted from the I/B/E/S database. The companies had to be in the NYSE and the AMEX.
b. The Acquiring and the target announcement data between 1986 and 1997 are from the SDC database.
c. At least 40 observations before an announcement and 10 observations after the announcement exist.

data will have at least one earnings announcement. After I match the companies in the earnings announcement sample with those in the acquisition announcement sample, there are 34,942 earnings announcements and 11,024 acquiring announcements. With companies existing both earnings announcement data and target announcement data, there are 30,618 earnings announcements and 4,877 target announcements. The number of observations after each filter is given in Table 1.

Since there are various measures of trading volume, one needs to be chosen. Since trading volume can be affected by the number of outstanding shares, I use turnover defined as in equation (1).[6] In this article, "trading volume" and "turnover" will be used interchangeably.

$$Turnover(\tau_{i,t}) = \frac{Trading \quad Volume_{i,t}}{The \quad Number \quad of \quad Outs\tan ding \quad Shares_{i,t}} \times 100 \tag{1}$$

The percentage deviation from the median turnover for the previous 30 trading days is used for the abnormal trading volume measure in this study and is defined as in equation (2). The reason to use a median in this analysis is large skewness

6) See Lo and Wang(2000) for systematic description of different measures of trading volume.

and kurtosis in turnover.

$$Abnormal \quad Turnover(\xi_{i,t}) = \frac{\tau_{i,t} - Median[\tau_{i,t-40}, \tau_{i,t-11}]}{Median[\tau_{i,t-40}, \tau_{i,t-11}]} \times 100 \quad (2)$$

In order to define abnormal trading volume and estimate it in an announcement window, I need at least 51 trading-day observations. Therefore, in all samples, only companies with 51 days of non-missing turnover are included in the final data set. To make an inference about abnormal trading volume, I compare median abnormal turnover from day t-10 to day t+10 with a bootstrapped distribution. Since the trading volume is highly autocorrelated,[7] I need to preserve the time series property when I generate a bootstrapped distribution.[8] I consider a block bootstrapping where the time series property of a series is sustained. Generating 630 random dates[9] and a random number of companies for each announcement day, I calculate 21-day abnormal trading volume series in each bootstrapping iteration. The p-values in tables are from the bootstrapped distribution of 1000 replications.

b. Empirical results

I obtain the median cross-sectional percentage deviation using median abnormal turnovers ($\xi_{i,t}$) from each company and make an inference using the bootstrapped distribution. Since turnover has a very fat tail (kurtosis is greater than 100) and an extreme positive skewness (greater than 7), a median would be a better estimator of a normal level of turnover than a mean.

The level of abnormal turnover in the period t-10 to t-3 is statistically significant with around 1% to 10% p-value for a one-side test as shown in Table 2. I find that a decrease of around 2 to 3% of daily trading volume, on average, prior to an earnings announcement. For summary measure, I construct the average of median abnormal turnover ($Median_i[\xi_{i,t}]$) in the period t-10 to

7) See Lo and Wang(2000).
8) Efron and Tibshirani(1983) provide a textbook for the bootstrap technique.
9) This is one quarter of observations in the original earnings announcements data.

Table 2. Median abnormal turnover around events

Announcements No.of Obs.	Earning 41,697	Acquisition 15,134	Target 8,448
$t = -10$	–1.024(0.094)	0.000(0.441)	5.747(0.000)
–9	–2.829(0.012)	0.919(0.044)	4.313(0.000)
–8	–2.515(0.030)	0.690(0.059)	6.255(0.000)
–7	–2.941(0.012)	1.155(0.034)	10.624(0.000)
–6	–2.837(0.014)	1.696(0.024)	11.565(0.000)
–5	–2.310(0.031)	0.527(0.064)	12.448(0.000)
–4	–1.673(0.052)	2.531(0.005)	14.496(0.000)
–3	–2.122(0.032)	0.658(0.064)	18.462(0.000)
–2	0.000(0.431)	2.921(0.005)	22.721(0.000)
–1	11.770(0.000)	6.725(0.000)	27.012(0.000)
0	46.868(0.000)	29.468(0.000)	119.461(0.000)
1	39.375(0.000)	26.445(0.000)	103.653(0.000)
2	19.184(0.000)	14.372(0.000)	59.521(0.000)
3	12.874(0.000)	9.415(0.000)	42.037(0.000)
4	10.006(0.000)	7.768(0.000)	31.650(0.000)
5	8.794(0.000)	6.225(0.000)	29.088(0.000)
6	6.017(0.000)	6.015(0.001)	23.904(0.000)
7	4.970(0.000)	3.401(0.007)	21.767(0.000)
8	3.108(0.004)	3.025(0.004)	17.623(0.000)
9	3.907(0.003)	1.606(0.042)	13.582(0.000)
$t = 10$	4.016(0.000)	1.734(0.023)	14.413(0.000)
Average of $t = [-10, -3]$	–2.281(0.001)	1.022(0.006)	9.411(0.000)

The abnormal turnover around each announcement from the companies in the NYSE and the AMEX between 1986 and 1997 is the percentage change between the annualized percentage turnover and the median annualized percentage turnover from t = –40 to t = –11. The p-values in parentheses are estimated from the bootstrapped distribution with 1000 iterations. They stand for the tail probability of the smaller side, i.e., their maximum is 0.5.

t-3 and observe that the negative turnover is large enough with *p*-value of much less than 1%. This implies that low turnover in a day is noticeable, but more importantly, a continuous streak of low turnover in this period is extraordinary.

To make it clear that the time series property of trading volume before a scheduled earnings announcement is extraordinary, I compare the result from earnings

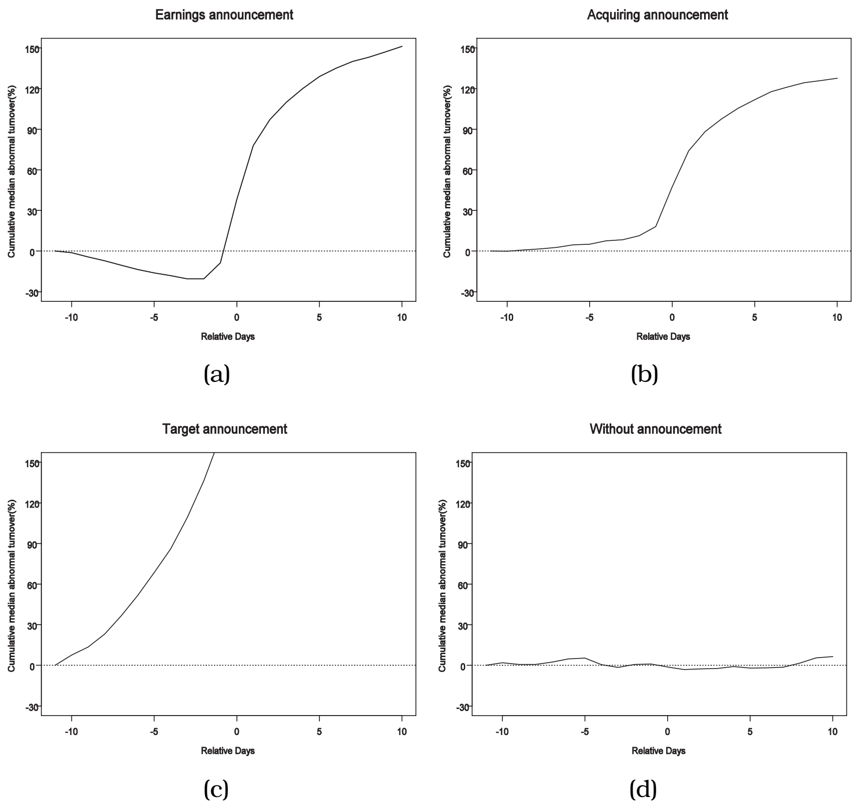


Figure 1. Cumulative median abnormal turnover from t = –10 to t = 10

In each announcement, percentage median abnormal turnovers compared to the median turnover from t = –40 to t = –11 are drawn. For Plot (d), the 72nd day from each earnings announcement is selected so that neither the estimaition window nor the event window includes an earnings announcement.

announcements with the results from two kinds of takeover announcements: an announcement that a firm is acquiring and an announcement that a firm is being targeted.[10] Obviously, the

10) I also examined 411 Moody's bond rating change announcements in 1997 and 1998. As expected, I could not observe the same pattern of trading volume as we can see in an earnings announcement. The turnover is almost stable or increased until the announcement day and increased on

time series patterns of these two announcements are different from those of scheduled earnings announcements. There is no negative abnormal trading volume prior to either type of announcement. Before these announcements, we can even observe statistically significant positive abnormal trading volume.[11] Compared with acquiring or target announcements where the trading volume increased prior to those announcements, the significance of the decreased trading volume before an earnings announcement is conspicuous.

For summary, I provide a plot of cumulative abnormal percentage turnover in the period from t = −10 to t = 10. In Figure 1(a), for 8 consecutive days, the turnover before an earnings announcement decreases about 20% cumulatively. However, in Figure 1(b) and 1(c) for acquiring and target announcements, we cannot observe any decrease pattern in the turnover for this period. Morever, the turnover has been increased considerably. In order to confirm that the measure of the abnormal turnover is appropriate, I choose a non-announcement day (here, 72nd day from each earnings announcement day) and a random number of companies from the earnings announcement data set, and do the same procedure as in the above investigation about three kinds of announcements. I carefully select the day so that the estimation and the event window do not include any earnings announcement date. In this case, only stable patterns of abnormal trading volume near zero can be observed, as shown in Figure 1(d). Therefore, our measure of abnormal turnover does not seem to be biased.

announcment days. Since Moody's rating change seems to follow the change of companies performance, the rating change can be expected and this might make it unclear the pattern of trading volume near an "unexpected" information announcement.

11) For an explanation of this positive trading volume, see Sanders and Zdanowicz(1992) or Jayaraman et al.(2001) etc.

3. Simple model

a. Model description

I suggest the following model to provide a theoretical explanation for the extraordinary trading volume pattern described in the previous section. This model is a simple extension of Kyle(1985) or Admati and Pfleiderer(1988), but contains an interesting feature regarding the market maker's inference and its result. I compare the two results from different assumptions about the knowledge of market participants.

There are four different player groups in this model: informed traders(IT), discretionary liquidity traders(DLT), naive liquidity traders(NLT), and a market maker(MM).

We begin by assuming that n informed traders, the IT, have the same information. The IT's information will be assumed to be $\tilde{\delta} + \tilde{\varepsilon}$, where $\tilde{\delta}$ is a normally distributed dividend with mean of zero in the final payoff, $\tilde{F} = \overline{F} + \tilde{\delta}$ (here, $\overline{F}$ is a constant part of final payoff), and $\tilde{\varepsilon}$, also normally distributed with mean of zero, is the noise in the IT's signal. With her information, $\tilde{\delta} + \tilde{\varepsilon}$, a risk-neutral IT decides her trading amount to maximize her final payoff. At the Nash equilibrium, an IT will submit a market order of $\tilde{x}_i = \beta_i (\tilde{\delta} + \tilde{\varepsilon})$.

Along with the IT, I assume that there are two types of liquidity traders, discretionary liquidity traders(DLT) and naive liquidity traders(NLT). These liquidity traders submit order flows $\tilde{y}$ and $\tilde{z}$, respectively. These two variables have mean of zero and positive variance. Only the DLT can react to the timing information in the market, i.e., they can react to the price sensitivity in MM's pricing function with consideration of their waiting cost.[12] If they recognize that the adverse selection cost is too high for their waiting cost, they will defer their order. Therefore, the concept of the DLT is justified only when they know the scheduled time of an information release. I conjecture

12) We can regard the DLT as investors who have relatively smaller waiting costs compared to the NLT when these two classes of uninformed liquidity investors want to defer a trade.

the equilibrium reaction from the DLT to be $\tilde{y} \cdot (\bar{\lambda} - \lambda) / \bar{\lambda}$, where $\bar{\lambda}$ is the maximum price sensitivity that can be reached when every DLT is ex ante out of the market and only the NLT remain.

The MM will set prices with the zero expected profit condition, as in Kyle(1985). The MM's decision is also affected by the timing information. If the MM cannot justify the existence of the DLT, and if even she does not know whether an announcement is impending or not, she will not consider the possibility of decreasing order flow from the DLT related to the size of the price sensitivity she will decide. Therefore, she will set up a pricing equation without any expectation of decreasing order flow from the DLT, as in Equation 3. In this case, the DLT end up behaving like the NLT.

Case 1: Unscheduled announcement

In this case, the DLT without timing information will behave like the NLT.

$$\tilde{P} = E[\bar{F} + \tilde{\delta} \mid \tilde{\Omega}^U]$$

$$\text{where, } \tilde{\Omega}^U = \sum_{i=1}^{n} \tilde{x}_i + \tilde{y} + z \tag{3}$$

If the MM knows when an announcement is to be issued, she rationally expects the existence of the DLT and reflects this in her inferences about the total order flow. Since the DLT do not want to trade much when the price sensitivity to the order flow is high, the MM will presume the smaller order flow from the DLT and set a different price sensitivity using the estimated DLT's order flow. This feature is formulated in Equation 4 as the presumed order flow, $\tilde{\Omega}^S$. This MM's improved price-setting mechanism will generate less variation of the price in the market and be consistent with one of the goals of the MM, maintaining the price continuity. To determine the maximum price sensitivity, $\bar{\lambda}$ in Equation 4, the case where there is no DLT ex ante should be investigated. In this case, the price sensitivity ($\bar{\lambda}$) will be decided from Equation 5.

Case 2: Scheduled announcement

Both DLT and NLT exist and only the DLT react to the price sensitivity.

$$\tilde{P} = E[\overline{F} + \tilde{\delta} \mid \tilde{\Omega}^S]$$

$$\text{where, } \tilde{\Omega}^S = \sum_{i=1}^{n} \tilde{x}_i + \frac{\overline{\lambda} - \lambda}{\overline{\lambda}} \tilde{y} + \tilde{z} \tag{4}$$

Case 3: Benchmark case

In this case, there exists only the NLT ex ante.

$$\tilde{P} = E[\overline{F} + \tilde{\delta} \mid \tilde{\Omega}^B]$$

$$\text{where, } \tilde{\Omega}^B = \sum_{i=1}^{n} \tilde{x}_i + \tilde{z} \tag{5}$$

According to the three cases, the price sensitivity to the order flow and the trading aggressiveness of the IT can be summarized in Lemma 1.

Lemma 1

If the MM knows the existence of DLT who are using a linear strategy of participation in the market, i.e., as in Case 2, the price sensitivity (λ^S) and IT's trading aggressiveness (β^S) in equilibrium will be the same as those from the limiting case, i.e., Case 3. Therefore, the price sensitivity in Case 2 is always larger than that in Case 1 and the trading aggressiveness in Case 2 is always less than that in Case 1.[13)]

$$\lambda^S = \overline{\lambda} > \lambda^U \tag{6}$$

$$\beta^S = \underline{\beta} < \beta^U \tag{7}$$

The interesting result is that this equilibrium value of λ^S and β^S is the same as the limiting values ($\overline{\lambda}$ and $\underline{\beta}$) from the case where there are no ex ante DLT and only the NLT exist. Since rationally behaving market participants with timing information

13) The proof for Lemma 1 is shown at the Appendix.

will drive the values of λ and β to the limiting values of Case 3, and thus, all of the DLT will escape from the market, in equilibrium.

With the equilibrium values of the price sensitivity and the trading aggressiveness, I measure the expected trading volume in the market in two cases, a scheduled announcement and an unscheduled announcement. I use the same volume measure as used in Admati and Pfleiderer(1988) or Foster and Viswanathan (1990). This measure is considered to be reasonable since it reflects the trading volume even between market participants other than the MM.

Proposition 1

If the MM can rationally expect the existence of the DLT, the expected trading volume will be less than that when she cannot.

$V^S < V^U$

where,

$$V^S = \sqrt{nVar(\tilde{z})} + \sqrt{Var(\tilde{z})} + \sqrt{(n+1)Var(\tilde{z})} \tag{8}$$

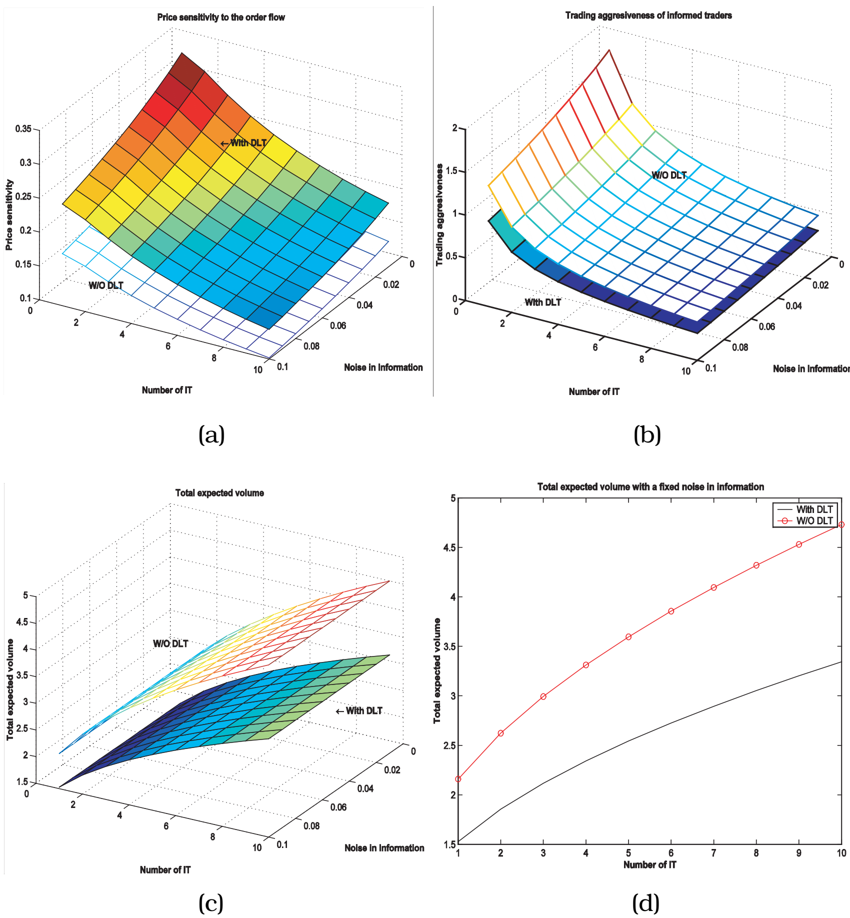
$$V^U = \sqrt{nVar(\tilde{y}) + Var(\tilde{z})} + \sqrt{Var(\tilde{y})} + \sqrt{Var(\tilde{z})} + \sqrt{(n+1)(Var(\tilde{y}) + Var(\tilde{z}))} \tag{9}$$

The reason for smaller trading volume in the case of a scheduled announcement is the DLT's escape from the market and the smaller trading volume from the IT.

Proof. Following the definition in Admati and Pfleiderer(1988) with β^S, λ^S, β^U, and λ^U in Lemma 1, we can calculate the expected trading volume using the variance of order flows from IT, DLT, and NLT and also the variance of total order flow observed by MM. Since the calculation of this is trivial, I save it for brevity. Q.E.D.

b. Implications of the model

With parameter values of Var($\tilde{\delta}$) = 0.1, Var($\tilde{y}$) = 0.2, Var($\tilde{z}$) = 0.2, and different values of Var($\tilde{\varepsilon}$) and n, the numerical values of λ and β from Lemma 1 are plotted in Figure 2. Plots (a) and (b)



"Price sensitivity" is denoted by λ, "Trading aggressiveness" by β, and "Noise in information" by $\mathrm{Var}(\tilde{\varepsilon})$. In (d), the noise in information ($\mathrm{Var}(\tilde{\varepsilon})$) is fixed at 0.05.

Figure 2. Numerical results of the model.

are for the price sensitivity to the order flow in the MM's pricing function and the trading aggressiveness in IT's order flow function. Plot (c) shows that the trading volume with scheduled announcements will be less than that with unscheduled ones. If I slice Plot (c) at $\mathrm{Var}(\tilde{\varepsilon}) = 0.05$, as in Plot (d), the relation between the expected trading volume and the number of the IT would be clearly demonstrated; if the number of IT is larger, the trading volume will be larger. With clear pictures of the proposition, I can state several testable hypotheses.

As a main hypothesis, the decreased trading volume before a scheduled announcement results from the discretionary liquidity trading generated from information asymmetry. Therefore, there should be a cross-sectional relationship between any measure of information asymmetry and the observed decreasing trading volume before a scheduled earnings announcement. Also, as shown in Figure 2(a), the price sensitivity to the order flow must be increased before an earnings announcement.

In the following section, I will investigate the relationship between the decreasing trading volume and both several information asymmetry proxies and the price sensitivity to the order flow. To support the information asymmetry explanation for the decreased trading volume, I provide another analysis related to risk measures around an announcement.

4. Cross-sectional analysis and robustness check

a. Cross-sectional analysis

Since I cannot directly measure the information asymmetry in the market, I investigate the relationship between the trading volume and several variables known to be good proxies for the information asymmetry, such as size, analyst coverage, and industry group.

As shown in Table 3, the decreasing trading volume before an earnings announcement disappears if more analysts cover a company. For example, before earnings announcements, when there are less than 6 analysts covering the companies, the turnover is decreasing almost 4% daily between $t = -10$ and $t = -3$, but when there are more than 10 analysts covering the companies, the turnover seems to slightly increase (daily 0.8%) in the same period. This relationship between the trading volume and the number of analysts is consistent with the hypothesis that there should be more trading accomplished when there is less information asymmetry before a scheduled announcement because the liquidity traders will stay in the market. Since analysts post their forecasts in various media,

Table 3. Median abnormal turnover according to the number of analyst estimation

No.of Est.	1-3	4-6	7-9	>9	Missing
No.of Obs.	16,896	9,068	5,942	6,718	1,621
t=-10	-2.908++	-0.344	-1.347+++	1.564**	-3.116+
-9	-4.177+	-4.178+	-2.685++	0.383***	-2.596++
-8	-3.244+	-4.818+	-3.052++	0.464***	-3.273+
-7	-4.567+	-3.854+	-3.354+	0.353***	-3.615+
-6	-4.165+	-4.140+	-3.012+	0.569***	-3.725+
-5	-4.325+	-4.682+	-1.379+++	0.621***	-0.510
-4	-1.660+++	-3.861+	-3.888+	1.098**	-0.738
-3	-2.921++	-3.810+	-2.675++	1.314**	-2.905++
-2	0.000	-2.904++	-1.182+++	3.587*	1.368**
-1	13.271*	8.390*	11.616*	12.854*	6.921*
0	52.031*	44.755*	44.753*	46.212*	31.571*
1	41.690*	40.071*	36.505*	40.107*	28.563*
2	19.481*	19.260*	18.943*	19.476*	17.067*
3	13.584*	13.404*	13.102*	11.592*	8.853*
4	10.761*	11.518*	10.628*	7.603*	6.687*
5	9.628*	11.148*	7.919*	7.446*	4.892*
6	6.647*	5.431*	5.763*	6.222*	3.894*
7	5.483*	6.415*	5.210*	2.638**	6.406*
8	3.613*	5.050*	1.982**	1.401**	4.915*
9	5.506*	3.333*	4.330*	1.633**	2.083**
t=10	3.722*	5.942*	3.147**	3.388*	3.596*
Average of t=[–10, –3]	-3.496	-3.711	-2.674	0.796	-2.560
p-value	0.000	0.000	-0.001	-0.011	-0.001

For the abnormal trading volume ($\xi_{i,t}$), the median turnover from t = –40 to t = –11 is calculated and subtracted from the turnover in the event window. The turnover is an annualized and percentage number of trading volume divided by shares outstanding. No. of Est. means the number of analysts who forecast the earnings announcement. +++, ++, and + mean respectively 10%, 5%, and 1% in the left tail of the bootstrapped distribution. ***, **, and * mean respectively 10%, 5%, and 1% in the right tail of the bootstrapped distribution.

individual investors can always obtain this information easily. If investors cannot find information with relatively small cost, they will consider themselves uninformed and will not participate in the market. In this case, discretionary liquidity traders prefer waiting for the scheduled information issuances.

Table 4. Median abnormal turnover according to the size quintile

Date	Small(20%)	2	3	4	Large(20%)
			Earningsannouncements		
No.of Obs.	6,900	8,842	9,121	8,804	9,238
t=(-10,-3)	-3.659+	-4.347+	-3.510+	-2.019+	-0.180
-2	1.597**	-1.053	-1.083	-0.163	2.156**
-1	18.132*	12.267*	9.377*	11.074*	11.635*
0	76.471*	55.176*	44.677*	45.088*	38.974*
1	51.875*	47.050*	42.959*	39.623*	31.205*
2	26.904*	20.593*	21.465*	20.099*	16.447*
t=[3,10]	8.667*	9.738*	7.357*	7.242*	5.108*
			Acquiring announcements		
No.of Obs.	2,949	2,664	2,781	2,892	3,848
t=[-10, -3]	2.775*	1.880*	-0.331	1.862*	0.226
-2	6.977*	2.922*	4.939*	-0.016	1.873**
-1	18.610*	5.940*	6.811*	4.619*	3.834*
0	70.902*	40.555*	31.907*	21.299*	14.507*
1	56.373*	29.049*	32.693*	22.555*	15.871*
2	29.809*	15.543*	13.750*	15.596*	10.046*
t=[3, 10]	8.540*	4.369*	4.580*	5.275*	3.987*
			Target announcements		
No.of Obs.	3,303	1,841	1,537	1,543	1,821
t=[-10, -3]	15.070*	18.640*	13.404*	14.836*	8.688*
-2	33.333*	26.272*	32.697*	27.378*	15.903*
-1	42.941*	38.881*	36.569*	31.058*	17.864*
0	223.530*	200.640*	143.240*	108.080*	65.968*
1	203.700*	156.350*	136.170*	96.457*	47.411*
2	113.830*	87.726*	75.844*	57.727*	28.221*
t=[3, 10]	35.443*	40.077*	42.600*	28.136*	14.995*

For the abnormal trading volume($\xi_{i,t}$), the median turnover from t=-40 to t=-11 is calculated and subtracted from the turnover in the event window. The turnover is an annualized and percentage number of trading volume divided by shares outstanding. Size break points are from Ken French's data base in http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/. +++, ++, and + mean respectively 10%, 5%, and 1% in the left tail of the bootstrapped distribution. ***, **, and * mean respectively 10%, 5%, and 1% in the right tail of the bootstrapped distribution.

Since the size of a company has been used as a proxy of information asymmetry in many studies(e.g. Hong, Lim and Stein(1998)), investigation of the relationship between the size of a company and the trading volume prior to each announcement is worthwhile. In Table 4, I report the result from an analysis using a size quintile offered by Ken French. As expected, only before an earnings announcement, can I notice the decreasing trading volume pattern, and this pattern is generally positively related to the company size.[14] In the smaller quintiles, around 3-4% decrease of trading volume is observed and, in the larger quintiles, the amount of decreased trading volume is attenuated to be about 1% or less.

Since the size of a company is believed to be related to the amount of analyst coverage, I investigate the trading volume pattern with respect to the company size and the analyst coverage in Table 5. I group the companies into 12 categories according to the size of the companies on $t = -10$ and the number of analysts. The sorting is done independently with the company size and the number of analysts. Between these two related variables, the number of analysts clearly gives the expected relationship with the decreasing trading volume pattern before an earnings announcement. On average, trading volume is decreased daily by 3 to 5% during the period of $t = -10$ to $t = -3$, and the degree of this decrease is monotonically weakened as the number of analysts increases in each size group. Only in the largest companies, does the number of analysts not show this same pattern of the trading volume.

According to the nature of a company's business, the earnings announcements from one company may not give as much new information as those from another company. For example, before an earnings announcement from a clothing company, uninformed traders have much less amount of information compared to an earnings announcement from a petroleum company. The performance of a petroleum company is heavily dependent on the market price of oil. This price is readily

14) Another interesting feature of this Table 4 is that the trading volume before an acquiring announcement and a target announcement is negatively related to the size of a company. This implies that there will be a different trading mechanism in those announcements compared to an earnings announcement.

Table 5. Median turnover according to the analyst coverage and the size

Size	Small30%			Medium40%			Large30%			Small	Medium	Large
No. Est.	1-3	4-6	>6	1-3	4-6	>6	1-3	4-6	>6		Missing	
No. Obs.	9,161	1,562	336	7,407	5,576	4,366	752	2,201	9,998	309	696	667
-10	-4.201+	0.000	-3.652+	-2.285++	-0.308	0.000	3.861*	-1.701+++	0.160	-11.320+	-4.188+	0.539
-9	-4.879+	-1.068	6.614*	-3.223+	-3.662+	-0.364	-1.552++	-5.259+	-0.591	-5.472+	-8.076+	2.268**
-8	-1.930++	-2.943++	-5.147+	-5.165+	-5.535+	-0.525	0.640	-2.322++	-0.287	-2.674++	-3.481+	-2.389++
-7	-3.695+	-4.384+	12.277*	-5.348+	-3.302+	-3.081++	-1.143+++	-3.871+	-0.408	-8.585+	-1.665+++	-1.986++
-6	-4.885+	-6.995+	2.905*	-4.033+	-4.511+	-3.427+	2.225**	-3.141++	0.479	-2.267++	-5.390+	-1.535+++
-5	-2.458++	-4.861+	4.726*	-6.867+	-4.909+	-0.295	2.538*	-4.210+	0.241	-9.602+	2.012**	-0.289
-4	-0.678	-3.480+	-1.138+++	-3.591+	-4.488+	-1.905++	5.406*	-1.848++	0.460	-2.243++	-3.593+	1.110**
-3	-2.171++	-3.236+	6.117*	-3.174+	-3.267+	-1.749++	-3.455+	-2.867++	0.516	-0.949+++	-4.215+	-0.048
-2	0.756	-0.268	2.885*	-0.691	-3.047++	-1.665+++	-0.431	-2.482++	2.938*	0.000	4.473*	-0.787
-1	15.340*	13.373*	28.386*	11.144*	8.366*	11.514*	9.589*	6.904*	12.686*	14.172*	6.764*	5.504*
0	67.679*	65.369*	93.680*	39.740*	47.398*	55.894*	40.344*	31.984*	43.254*	60.779*	37.045*	23.092*
1	48.668*	54.064*	71.126*	37.232*	44.195*	50.925*	32.392*	29.613*	35.898*	42.184*	37.963*	23.285*
2	23.271*	24.549*	35.516*	17.405*	21.490*	26.078*	11.748*	16.054*	18.281*	23.260*	19.550*	15.726*
3	15.922*	18.564*	14.393*	12.390*	15.182*	15.772*	3.775*	9.410*	11.871*	13.874*	15.362*	4.645*
4	13.640*	16.660*	20.875*	9.238*	11.502*	11.121*	7.166*	8.812*	8.645*	10.083*	9.389*	5.032*
5	11.245*	18.603*	6.474*	8.745*	12.466*	9.846*	8.031*	7.162*	7.652*	8.521*	5.205*	4.892*
6	8.504*	5.403*	5.224*	5.239*	6.724*	9.519*	5.019*	2.247**	5.930*	-3.154++	5.877*	6.821*
7	6.019*	9.556*	4.778*	5.834*	7.859*	5.139*	4.445*	2.859*	3.990*	0.603***	9.571*	6.602*
8	4.075*	10.254*	8.742*	3.237*	5.505*	2.004**	5.135*	2.361**	2.010**	2.130**	4.534*	7.912*
9	5.580*	4.535*	6.523*	7.246*	4.892*	5.235*	-0.898*	1.266**	2.803**	6.202*	4.597*	-0.058
10	4.485*	6.359*	22.104*	3.288*	6.729*	3.894*	1.045***	5.544*	3.890*	-4.504+	7.140*	0.880***
Average of t=[-10, -3]	-3.112	-3.371	2.838	-4.211	-3.748	-1.418	1.065	-3.152	0.071	-5.389	-3.575	-0.291
p-value	0.000	0.000	0.000	0.000	0.000	-0.009	-0.005	0.000	-0.235	0.000	0.000	-0.438

For the abnormal trading volume($\xi_{i,t}$), the median turnover from t=-40 to t=-11 is calculated and subtracted from the turnover in the event window. The turnover is an annualized and percentage number of trading volume divided by shares outstanding. No. Est. means the number of analysts who forecasted the earnings announcement. +++, ++, and + mean respectively 10%, 5%, and 1% in the left tail of the bootstrapped distribution. ***, **, and * mean respectively 10%, 5%, and 1% in the right tail of the bootstrapped distribution.

Table 6. Median abnormal turnover according to industry

Date	Agriculture, Forest, Fish, Mine	Construction, Material	Food, Tobacco	Textile, Clothing, Consumption	Logging, Paper Publishing	Chemical	Petroleum
Earnings announcement matching with acquiring							
No.of Obs.	1,587	2,992	1,029	1,655	1,915	2,032	384
t=[-10, -3]	-1.187++	-3.004+	-3.144+	-6.163+	-0.564	-1.773+	4.466*
-2	-1.332+++	-0.280	-2.125++	2.356**	0.517	0.000	-4.943+
-1	5.765*	14.539*	10.320*	25.311*	11.564*	13.228*	4.703*
0	24.027*	46.430*	37.905*	72.594*	45.589*	39.972*	12.802*
1	16.217*	36.619*	30.084*	59.485*	38.376*	31.296*	7.725*
2	11.084*	21.571*	16.687*	29.324*	18.832*	15.934*	7.881*
t=[3, 10]	-0.009	7.474*	5.145*	8.009*	9.640*	3.866*	-0.795++
Acquiring announcement matching with earnings							
No.of Obs.	384	687	378	381	581	693	62
t=[-10, -3]	2.574*	3.884*	0.666**	4.575*	0.363	0.267	7.850*
-2	-2.022+++	9.271*	1.941	0.148	6.542*	3.847*	2.118**
-1	8.711*	16.173*	8.643*	10.112*	3.588*	4.657*	5.086*
0	41.383*	40.724*	14.741*	46.301*	20.283*	18.749*	3.391*
1	31.017*	36.990*	17.211*	44.621*	25.921*	16.633*	22.921*
2	15.853*	20.679*	5.078*	29.551*	8.387*	11.402*	20.028*
t=[3, 10]	8.415*	8.217*	1.087*	7.315*	1.373*	1.998*	8.499*
Earnings announcement with target							
No.of Obs.	1,286	2,461	995	1,598	1,764	1,914	341
t=[-10, -3]	0.130	-2.729+	-2.825+	-5.991+	-0.750++	-1.410+	3.871*
-2	-1.310+++	0.714	-1.526+++	2.429**	1.589**	0.706	-4.495+
-1	7.225*	13.565*	10.384*	26.727*	11.687*	13.286*	1.243*
0	24.973*	44.253*	37.905*	72.674*	44.160*	40.904*	12.510*
1	15.729*	35.003*	29.613*	60.443*	38.727*	33.650*	5.550*
2	12.015*	20.607*	15.874*	29.616*	18.055*	17.160*	5.762*
t=[3, 10]	-0.115	7.218*	4.548*	7.725*	9.870*	4.163*	-2.366+
Target announcement matching with earnings							
No.of Obs.	180	423	160	263	261	352	67
t=[-10, -3]	10.848*	24.198*	8.660*	10.813*	9.332*	4.912*	14.448*
-2	10.174*	43.478*	20.283*	17.416*	29.424*	19.275*	17.188*
-1	10.804*	40.000*	19.477*	46.274*	23.774*	15.126*	7.100*
0	82.141*	159.870*	79.557*	204.150*	59.593*	70.790*	49.852*
1	52.925*	110.340*	49.159*	174.700*	47.411*	37.448*	92.991*
2	61.633*	48.000*	30.666*	81.343*	20.502*	37.779*	34.135*
t=[3, 10]	26.751*	29.792*	2.291*	20.478*	10.441*	11.423*	2.426*

Table 6. continued

Date	Machinery, Equipment, Computer	Trans-portation	Utility Telecommuni-cation	Wholesale Retail	Finance	Conglomerate Entertainment Services
			Earnings announcement matching with acquiring			
No.of Obs.	4,606	1,384	1,930	3,250	4,218	2,384
t=[-10, -3]	-0.869++	-2.506+	-2.196+	-1.980+	-3.497+	-1.333++
-2	4.124*	0.345	1.972**	2.663*	-0.852	0.035
-1	18.963*	16.304*	4.556*	18.307*	11.286*	13.813*
0	65.702*	49.940*	16.040*	64.900*	42.073*	67.774*
1	51.309*	36.373*	16.979*	50.924*	38.784*	52.481*
2	20.908*	19.279*	9.200*	24.992*	18.628*	20.899*
t=[3, 10]	8.756*	4.374*	6.066*	7.212*	5.639*	6.040*
			Acquiring announcement matching with earnings			
No.of Obs.	1,398	394	323	727	1,461	867
t=[-10, -3]	3.621*	0.582	3.717*	-0.670+++	0.388	-3.265+
-2	5.328*	-1.702+++	1.227**	0.000	1.017**	1.083**
-1	9.347*	9.179*	10.965*	-1.446+++	7.392*	0.470***
0	27.854*	27.941*	15.525*	38.802*	23.832*	37.612*
1	25.427*	20.555*	11.813*	28.094*	22.396*	34.601*
2	12.416*	3.099*	12.829*	15.438*	11.683*	18.640*
t=[3, 10]	5.941*	3.613*	3.809*	1.567*	3.276*	4.463*
			Earnings announcement with target			
No.of Obs.	4,490	1,488	1,540	2,958	3,639	2,057
t=[-10, -3]	-1.127++	-1.689+	-1.509+	-2.648+	-3.278+	-0.914++
-2	3.156*	1.345**	2.021**	1.722**	-1.631+++	-1.831+++
-1	16.548*	16.430*	5.040*	17.883*	11.045*	15.301*
0	62.869*	50.000*	19.956*	62.082*	43.051*	65.600*
1	51.229*	37.999*	19.162*	49.721*	40.356*	51.445*
2	21.615*	19.950*	9.938*	22.637*	18.092*	19.850*
t=[3, 10]	8.030*	5.716*	7.944*	7.466*	6.103*	6.136*
			Target announcement matching with earnings			
No.of Obs.	758	296	143	418	686	390
t=[-10, -3]	9.554*	9.790*	8.538*	11.588*	10.783*	11.907*
-2	26.073*	9.401*	22.838*	23.887*	24.938*	28.885*
-1	25.353*	24.176*	18.023*	25.192*	22.931*	33.281*
0	116.660*	113.450*	51.037*	143.990*	85.217*	138.780*
1	89.901*	91.236*	58.765*	110.490*	59.905*	137.240*
2	46.141*	38.539*	51.240*	50.049*	32.869*	77.549*
t=[3, 10]	15.131*	22.762*	21.073*	21.287*	13.554*	36.220*

For the abnormal trading volume($\xi_{i,t}$), the median turnover from t = –40 to t = –11 is calculated and subtracted from the turnover in the event window. The turnover is an annualized and percentage number of trading volume divided by shares outstanding. The industry categorization method is from Lewellen(1999). +++, ++, and + mean respectively 10%, 5%, and 1% in the left tail of the bootstrapped distribution. ***, **, and * mean respectively 10%, 5%, and 1% in the right tail of the bootstrapped distribution.

available and oil futures market provides considerable information to every investor in the market. The uninformed traders or discretionary liquidity traders do not need to react to this oil company's earnings announcement as much as to an earnings announcement of another company whose performance they cannot easily estimate. As shown in Table 6, prior to the earnings announcement from a petroleum company, uninformed traders do not worry about the informed traders' informational advantage and stay in the market. We can also observe this phenomenon in industries such as agriculture, paper, and retailing industries, which have relatively widely published information about the future cash flows of the company before their earnings announcements, even though the time series patterns in those industries are not as clear as ones in the petroleum industry.

For the price sensitivity measure, absolute return divided by absolute turnover is used. Even though this measure does not exactly match the concept of λ in the model, using it still gives the same qualitative implications and greater convenience of the test. Since a turnover can sometimes be zero, if there is a non-zero return with a zero turnover, I arbitrarily assign a large number. Since I measure the normal level of the price sensitivity using median values, this arbitrarily large number does not cause any bias, if we can assume that the price sensitivity in this case is at least larger than the median.

$$\text{Price Sensitivity } (\lambda_{i,t}) = \frac{|r_{i,t}|}{\tau_{i,t}} \tag{10}$$

For abnormal price sensitivity, I use a similar measure to the abnormal trading volume. It is defined as the percentage deviation from the median price sensitivity from the previous 30 trading days as shown in Equation 11. If the median of 30-day price sensitivity is zero, I exclude that data series from the sample. This will definitely create a bias in the sample, but the bias goes against my hypothesis. Therefore, to use this measure is conservative.

Table 7. Median abnormal price sensitivity around events

Date No.of Obs.	Earning 41,689	Acquisition 15,120	Target 8,448
-10	0.952(0.142)	-0.099(0.012)	-4.204(0.000)
-9	2.595(0.044)	-0.766(0.005)	-6.057(0.000)
-8	2.936(0.030)	-2.258(0.001)	-7.119(0.000)
-7	3.514(0.021)	-0.381(0.008)	-6.044(0.000)
-6	1.850(0.074)	-0.578(0.009)	-8.007(0.000)
-5	2.030(0.064)	0.000(0.413)	-9.541(0.000)
-4	3.453(0.017)	-0.442(0.014)	-11.992(0.000)
-3	4.520(0.007)	0.000(0.412)	-11.814(0.000)
-2	2.305(0.038)	-0.358(0.020)	-14.570(0.000)
-1	-0.730(0.012)	-1.700(0.005)	-16.351(0.000)
0	-14.862(0.000)	-13.383(0.000)	-35.390(0.000)
1	-17.074(0.000)	-14.090(0.000)	-41.810(0.000)
2	-11.811(0.000)	-12.094(0.000)	-36.988(0.000)
3	-7.538(0.000)	-7.516(0.000)	-27.763(0.000)
4	-6.722(0.000)	-7.451(0.000)	-22.484(0.000)
5	-6.787(0.000)	-6.102(0.000)	-25.939(0.000)
6	-5.149(0.000)	-4.133(0.000)	-20.172(0.000)
7	-4.773(0.000)	-5.339(0.000)	-17.540(0.000)
8	-3.146(0.002)	-3.772(0.001)	-13.246(0.000)
9	-2.391(0.006)	-3.132(0.002)	-9.214(0.000)
10	-2.863(0.002)	-2.352(0.007)	-12.169(0.000)
Average of t=[-10, -3]	2.731(0.000)	-0.566(0.002)	-8.097(0.000)

The abnormal price sensitivity around each announcement from the companies in the NYSE and the AMEX between 1986 and 1997 is the percentage change between the price sensitivity and the median price sensitivity from $t = -40$ to $t = -11$. The p-values are estimated from the bootstrapped distribution with 1000 iterations. They stand for the tail probability of the smaller side, i.e., their maximum is 0.5.

$$\text{Abnormal Price Sensitivity } (\varphi_{i,t})(\%) = \frac{\lambda_{i,t} - Median[\lambda_{i,t-40}, \cdots, \lambda_{i,t-11}]}{Median[\lambda_{i,t-40}, \cdots, \lambda_{i,t-11}]} \times 100 \tag{11}$$

In Table 7, we can observe higher price sensitivity only prior to earnings announcements. The p-value is also around 1 to 5% and statistically significant. Compared with an acquisition announcement or a target announcement, a scheduled earnings announcement drives liquidity traders to become discretionary and the market maker to recognize the existence of these discretionary liquidity traders, as shown in the model. Therefore, the price sensitivity will be higher only before scheduled announcements. This result also supports the information asymmetry explanation of the decreased trading volume before an earnings announcement.

b. Other explanations of decreased trading volume

Given various empirical results about the increasing volatility around earnings announcements(e.g., Donders and Vorst (1996)), there may exist other explanations about the reasons for the decreased trading volume before scheduled earnings announcements. In a hypothetical world in which there is no information asymmetry, investors will trade securities with allocational and/or liquidity motives. If investors with allocational motives know there will be higher risk in the future, they may have an incentive to change their position and generate trading volume in the market. Even though this explanation requires several assumptions about investors, such as risk averse investors, it is worthwhile to check if there is another explanation for the decreased trading volume before an earnings announcement.

In Table 8, I group the companies into quintiles according to the standard deviations or betas[15] estimated from the periods $t = -70$ to -11 or from $t = 11$ to $t = 70$.[16] With the risk-averse investor explanation, less turnover should be observed with the higher volatility or beta estimated especially in the post-announcement period. However, as shown in the table, we cannot find the anticipated relationship between the trading volume and risk measures, such as the standard deviation of return or the beta. Therefore, I believe that I can exclude the possibility of the risk-based explanation of the decreasing

15) Since there might be an incorrect estimation of beta because of infrequent trading in daily data, I used Dimson(1979)'s adjusted beta.

16) I also implement alternative windows of $t = -1$ to -70 and $t = 1$ to 70 or $t = -1$ to -150 and $t = 1$ to 150 for the pre and the post period. The results were almost the same.

Table 8. Abnormal turnover according to risk measures

Date	Small	2	3	4	Large
		Volatility between t=-70 and t=-11			
No. Obs.	8,260	8,488	8,744	8,447	8,488
t=[-10, -3]	-0.578	-2.086+	-1.405+	-6.991+	0.937
-2	5.149*	0.000	-1.116*	-5.553+	5.207*
-1	15.648*	12.086*	10.043*	9.266*	14.595*
0	58.668*	42.419*	41.570*	40.189*	58.882*
1	53.386*	35.945*	34.925*	29.261*	51.088*
2	28.064*	18.755*	12.899*	13.187*	28.176*
t=[3, 10]	13.375*	5.819*	2.100*	2.179*	13.957*
		Volatility between t=11 and t=70			
No. Obs.	8,360	8,579	8,517	8,477	8,494
t=[-10, -3]	-4.26+	0.796	-1.539+	-4.165+	-0.584
-2	-2.023++	4.118*	1.414**	-2.107++	1.150**
-1	12.307*	14.497*	15.415*	6.660*	11.905*
0	45.546*	54.020*	52.968*	40.205*	46.782*
1	33.531*	49.045*	42.479*	33.749*	44.254*
2	13.192*	28.620*	23.432*	12.899*	22.963*
t=[3, 10]	4.324*	9.001*	9.398*	1.283*	11.791*
		Beta between t=-70 and t=-11			
No. Obs.	8,485	8,486	8,485	8,486	8,485
t=[-10, -3]	-1.931+	-1.27++	-1.359++	-2.436+	-2.758+
-2	-1.000	1.054*	0.000	0.486***	2.355**
-1	5.167*	8.688*	12.133*	14.122*	19.221*
0	44.971*	45.055*	45.293*	48.982*	54.892*
1	39.092*	41.897*	39.861*	39.473*	41.976*
2	21.081*	18.419*	20.498*	21.860*	19.018*
t=[3, 10]	8.079*	8.915*	6.973*	6.361*	5.644*
		Beta between t=11 and t=70			
No. Obs.	8,485	8,486	8,485	8,486	8,485
t=[-10, -3]	-3.412+	-2.356+	-2.204+	-0.952++	-0.861+++
-2	-1.195+++	-0.644	-0.131	3.045*	2.569*
-1	5.700*	10.833*	11.441*	15.693*	15.889*
0	41.408*	44.928*	46.629*	48.346*	58.250*
1	34.253*	39.305*	43.238*	41.517*	44.391*
2	19.117*	18.691*	20.413*	20.244*	22.614*
t=[3, 10]	6.405*	7.180*	7.826*	7.779*	6.410*

For the abnormal trading volume ($\xi_{i,t}$), the median turnover from $t = -40$ to $t = -11$ is calculated and subtracted from the turnover in the event window. The turnover is an annualized and percentage number of trading volume divided by shares outstanding. No. of Est. means the number of analysts who forecast the earnings announcement. +++, ++, and + mean respectively 10%, 5%, and 1% in the left tail of the bootstrapped distribution. ***, **, and * mean respectively 10%, 5%, and 1% in the right tail of the bootstrapped distribution. The used risk measures are volatility and beta estimated from $t = -70$ to $t = -11$.

trading volume before a scheduled announcement.

c. Robustness check

Since I compare different announcement databases, there might be unobserved different characteristics of companies in each announcement sample. To control for any firm-specific

Table 9. Median abnormal turnover around events after matching

Announcements matchingwith	Earnings acquiring	Acquisition earnings	Earnings target	Target earnings
No.of Obs.	34,942	11,024	30,618	4,877
t=-10	-0.870(0.106)	0.396(0.045)	-0.939(0.103)	4.451(0.000)
-9	-2.904(0.011)	0.363(0.064)	-2.670(0.014)	3.028(0.000)
-8	-2.801(0.019)	1.302(0.027)	-2.026(0.050)	5.760(0.000)
-7	-3.353(0.008)	1.129(0.029)	-3.061(0.010)	9.435(0.000)
-6	-2.843(0.014)	2.318(0.015)	-2.306(0.029)	10.898(0.000)
-5	-2.288(0.031)	0.369(0.070)	-1.774(0.065)	10.858(0.000)
-4	-1.948(0.039)	2.561(0.005)	-1.421(0.068)	12.938(0.000)
-3	-2.120(0.032)	0.452(0.076)	-2.041(0.034)	16.920(0.000)
-2	0.000(0.457)	2.301(0.013)	0.137(0.097)	20.522(0.000)
-1	12.335(0.000)	6.407(0.000)	12.448(0.000)	23.740(0.000)
0	47.979(0.000)	27.872(0.000)	48.162(0.000)	97.082(0.000)
1	39.587(0.000)	25.721(0.000)	40.299(0.000)	77.261(0.000)
2	19.538(0.000)	14.211(0.000)	19.134(0.000)	44.409(0.000)
3	13.008(0.000)	9.185(0.000)	13.655(0.000)	30.574(0.000)
4	10.175(0.000)	7.072(0.000)	10.418(0.000)	23.207(0.000)
5	8.741(0.000)	5.946(0.000)	8.936(0.000)	21.624(0.000)
6	6.014(0.000)	6.045(0.000)	6.389(0.000)	17.266(0.000)
7	4.656(0.002)	3.424(0.007)	5.100(0.001)	14.350(0.000)
8	2.738(0.006)	2.480(0.013)	2.860(0.006)	12.512(0.000)
9	3.775(0.004)	1.613(0.042)	3.913(0.003)	8.907(0.000)
t=10	4.260(0.000)	1.394(0.037)	4.333(0.000)	9.541(0.000)
Average of t=[-10, -3]	-2.391(0.001)	1.111(0.003)	-2.030(0.001)	9.286(0.000)

The abnormal turnover around each announcement from the companies in the NYSE and the AMEX between 1986 and 1997 is the percentage change between the annualized percentage turnover and the median annualized percentage turnover from $t = -40$ to $t = -11$. The p-values in parentheses are estimated from the bootstrapped distribution with 1000 iterations. They stand for the tail probability of the smaller side, i.e., their maximum is 0.5.

Table 10. Robustness check

Panel A: Using larger estimation windo(t=–55to-11)

Announcement	Earnings	Acquiring	Target
No. of Obs.	42,776	14,967	10,007
t=[-10, -3]	-3.107+	1.314*	15.337*
-2	-0.047	2.956*	28.350*
-1	10.613*	6.891*	35.556*
0	47.355*	29.988*	143.450*
1	39.679*	26.843*	125.680*
2	19.473*	14.839*	75.146*
t=[3, 10]	6.269*	5.327*	31.982*

Panel B: Using mean abnormal log (turnover)

Announcement	Earnings	Acquiring	Target
No. of Obs.	37,675	13,307	8,239
t=[-10, -3]	-1.741+	2.527*	17.003*
-2	1.637*	5.194*	27.800*
-1	11.984*	7.830*	34.998*
0	41.118*	30.475*	99.202*
1	35.712*	26.063*	92.520*
2	19.355*	16.086*	62.269*
t=[3, 10]	7.558*	5.871*	30.415*

Panel C: Using sub-period

Announcement	Earnings			Acquiring			Target		
Subperiod	1986-89	1990-93	1994-97	1986-89	1990-93	1994-97	1986-89	1990-93	1994-97
No. of Obs.	10,616	12,385	18,559	3,534	3,919	7,607	4,614	2,088	3,354
t=[-10, -3]	-1.260**	-1.963+	-3.366+	4.230*	-0.780+++	0.574**	24.015*	5.828*	7.460*
-2	6.829*	0.691***	-3.659+	5.787*	0.340***	2.666*	44.561*	13.255*	15.354*
-1	29.999*	14.286*	0.757***	11.245*	4.442*	5.994*	60.000*	12.893*	21.962*
0	30.504*	53.669*	54.430*	35.646*	21.963*	30.305*	233.100*	79.571*	94.084*
1	19.699*	40.523*	52.474*	33.333*	21.851*	25.378*	221.740*	60.512*	82.604*
2	10.096*	23.952*	22.681*	20.165*	10.540*	13.893*	128.410*	33.333*	48.519*
t=[3, 10]	4.046*	8.575*	7.125*	8.089*	2.252*	4.879*	51.420*	10.673*	20.308*

For the abnormal trading volume, except for panel B where log(turnover) and mean abnormal turnover are used, the median turnover in the estimation period(45 days in panel A and 30 days in panel C) is calculated and subtracted from the turnover in the event window. The turnover is an annualized and percentage number of trading volume divided by shares outstanding. In panel A and C, +++, ++, and + mean respectively 10%, 5%, and 1% in the left tail of the bootstrapped distribution. ***, **, and * mean respectively 10%, 5%, and 1% in the right tail of the bootstrapped distribution. In panel B, +++, ++, +, ***, **, and * are from the t-distribution.

characteristics, I match companies in the earnings announcement sample and in the acquiring or the target announcement sample. However, the result from the matching sample shows a stronger pattern of decreasing trading volume only before an earnings announcement, as in Table 9. Before matching, the average of the median abnormal turnover from t = –10 to t = –3 is –2.281%. It is slightly increased to –2.391% when the data are matched with the acquiring announcement sample and slightly decreased into –2.030% when the data are matched with the target announcement sample.

For the normal level of turnover, the estimation window in this paper is the period from t = –40 to t = –11. As a robustness check, I attach a summarized table in Panel A of Table 10 from a longer estimation window from t = –55 to t = 11. In this table, the result is greatly strengthened, with –3.107% decrease from the normal level of turnover.

Another robustness check involves the use of median and the bootstrapped distribution. In Panel B of Table 10, I apply a conventional approach of an event study where the mean abnormal measure and the t-distribution are used.[17] The difference of the natural log of turnover and the natural log of the normal level turnover is statistically significantly negative only before an earnings announcement.

As a robustness check of the stability of this specific pattern, I provide the subperiod results in Panel C of Table 10. Among three subperiods, only in the earliest period of 1986-1989, the significance level is 5%. In the other two subperiods, the median abnormal turnover is decreased around 2-3% with less than 1% significance level. Before either an acquiring or a target announcement, I do not observe this interesting and intuitive trading volume pattern.

5. Conclusion

Using the I/B/E/S earnings announcement and the SDC

17) In order to deal with the skewness of turnover, I use the natural log. Because there are many zero turnovers in the sample, I use the negative value of the maximum of log(turnover) for the value of log(zero turnover). This will make the entire distribution almost symmetric.

takeover announcement data from 1986 to 1997, I find that the decreasing trading volume exists only before a scheduled earnings announcement. Constructing a simple and intuitive model, this interesting pattern of trading volume can be explained as resulting from the information asymmetry and the trading behavior of discretionary liquidity traders. I relate the trading volume pattern with proxies of the ex ante information asymmetry. The proxies such as analyst coverage, size, and industry categorization are all correspondingly related with the trading volume only before a scheduled announcement. However, between analyst coverage and size, analyst coverage shows a clearer cross-sectional relationship with the trading volume pattern.

I investigate the trading volume and risk measures(volatility and risk) to differentiate two possible explanations of the decreasing trading volume: the information asymmetry explanation vs. the risk-based explanation. The result from the investigation of risk measures excludes the latter explanation. Also, following the logic of the model, the absolute return divided by turnover(a measure of price sensitivity) increases only before an earnings announcement; this makes the information asymmetry explanation, as in the model, much more plausible.

The robustness of the methodologies in this study has been carefully probed, and I believe that I have shown an economically intuitive trading volume pattern to be related to another kind of hitherto unexplored information, the timing information. Even with different estimation windows, mean abnormal log turnover, and varying sub-periods, the main result of this paper is preserved. Unlike most anomalies in financial economics, this specific pattern seems to be even more pronounced in recent sub-periods.

I conclude that the timing information provides discretionary liquidity traders with an opportunity for trading optimization under information asymmetry and that this causes a decrease of trading volume only before a scheduled announcement. Two remaining questions of interest, the return implication of this timing information asymmetry and the identification of escaping traders using a specific data set, will be explored in my further research in progress.

Appendix

Since the current model is a modified model from Admati and Pfleiderer(1988) or Kyle(1984, 1985), so my notation conforms with that in Admati and Pfeiderer(1988) or Kyle(1984, 1985).

Proof of Lemma 1

To calculate the aggressiveness of trading by informed traders (β) and the price sensitivity to the order flow of the market maker (λ), we need to use two conditions; informed traders' expected profit maximization and the market maker's zero profit condition.

For the informed traders' decision, they will maximize the expected profits,

$$E[x_i(\tilde{F} - P(\tilde{\Omega})) \mid \tilde{\delta} + \tilde{\varepsilon}]$$

where $P(\tilde{\Omega}) = E[\tilde{F}] + \lambda\tilde{w} = \overline{F} + \lambda\tilde{w}$, $\tilde{w} = \sum_{i=1}^{N} x_i + \tilde{y} + \tilde{z}$

and $$\tilde{\Omega} = \sum_{i=1}^{N} \tilde{x}_i + \tilde{y} + \tilde{z} \tag{A1}$$

$$E[x_i(\tilde{\delta} - \lambda(\sum_{i=1}^{N} x_i + \tilde{y} + \tilde{z})) \mid \tilde{\delta} + \tilde{\varepsilon}] \tag{A2}$$

The ith informed investor will conjecture the market order of other $N - 1$ informed traders as $\beta(\tilde{\delta} + \tilde{\varepsilon})$. Therefore, the total order flow is $x_i + (N-1)\beta(\tilde{\delta} + \tilde{\varepsilon}) + \tilde{y} + \tilde{z}$. So, ith informed investors will choose x_i to maximize

$$E[x_i(\tilde{\delta} - \lambda(x_i + (N-1)\beta(\tilde{\delta} + \tilde{\varepsilon}) + \tilde{y} + \tilde{z})) \mid \tilde{\delta} + \tilde{\varepsilon}] \tag{A3}$$

To maximize this, x_i is set to equal to

$$\left(\frac{Var[\delta]}{2\lambda(Var[\delta] + Var[\varepsilon])} - \frac{(N-1)\beta}{2}\right)(\tilde{\delta} + \tilde{\varepsilon}) \tag{A4}$$

Since this should be equal to $\beta(\tilde{\delta} + \tilde{\varepsilon})$, the aggressiveness of informed traders (β) will be

$$\beta = \frac{Var[\delta]}{\lambda(n+1)(Var[\delta] + Var[\varepsilon])} \tag{A5}$$

The information set for informed investors is a noisy signal ($\tilde{\delta} + \tilde{\varepsilon}$) and the conditional expectation of the order flow of DLT and NLT are zero on this signal, so the profits maximization for informed traders will not be changed from an unscheduled announcement case to scheduled announcement case. However, the market maker's pricing problem will be changed since her information set is order flow ($\tilde{w}$). The investigation for an unscheduled announcement case, a benchmark case, and a scheduled announcement case follows.

First, before unscheduled announcements, discretionary liquidity traders cannot behave as discretionary liquidity traders ($\tilde{y}$) since they cannot detect an incoming announcement, they will behave as naive traders ($\tilde{z}$). Therefore, the market maker's observed order flow will be

$$\tilde{w} = \sum_{i=1}^{N} x_i + \tilde{y} + \tilde{z} \tag{A7}$$

In a competitive market making industry, the expected profit should be zero. This implies

$$P(\tilde{\Omega}) = E[\tilde{F}] + \lambda\tilde{w} = E[\tilde{F} \mid \tilde{w}] = \overline{F} + \frac{Cov[\tilde{\delta}, \tilde{w}]}{Var[\tilde{w}]}\tilde{w} \tag{A8}$$

So, the price sensitivity of order flow (λ) will be decided by covariance of dividend in the future and order flow and variance of order flow.

$$\lambda^U = \frac{N\beta Var[\tilde{\delta}]}{N^2\beta^2(Var[\tilde{\delta}] + Var[\tilde{\varepsilon}]) + Var[\tilde{y}] + Var[\tilde{z}]} \tag{A9}$$

With (A5) and (A9), the unique and positive price sensitivity of order flow (λ) is found in a third order equation as (A10).

$$\lambda^U = \frac{Var[\tilde{\delta}]}{(N+1)}\sqrt{\frac{N}{(Var[\tilde{\delta}]+Var[\tilde{\varepsilon}](Var[\tilde{y}]+Var[\tilde{z}])}} \tag{A10}$$

Once the price sensitivity to order flow (λ) for an unscheduled announcement case is found, the trading aggressiveness of informed traders (β) will be as in (A11).

$$\beta^U = \sqrt{\frac{Var[\tilde{y}]+Var[\tilde{z}]}{N(Var[\tilde{\delta}]+Var[\tilde{\varepsilon}])}} \tag{A11}$$

Second, as a benchmark case, if there are initially no discretionary liquidity traders (so, no $\tilde{y}$ in the model), there will be only naive liquidity traders ($\tilde{z}$). This case can be understood as the case with the lowest liquidity in the market.

With similar informed traders' profit maximization problem and the market maker's zero profit condition, the price sensitivity to order flow (λ) and the trading aggressiveness of informed traders (β) will be (A12) and (A13), respectively.

$$\overline{\lambda} = \frac{Var[\tilde{\delta}]}{(N+1)}\sqrt{\frac{N}{(Var[\tilde{\delta}]+Var[\tilde{\varepsilon}]Var[\tilde{z}]}} \tag{A12}$$

$$\underline{\beta} = \sqrt{\frac{Var[\tilde{z}]}{N(Var[\tilde{\delta}]+Var[\tilde{\varepsilon}])}} \tag{A13}$$

Third, with a scheduled announcement, the market maker will consider the existence of discretionary liquidity traders when she decides the price. Therefore, the market maker's observed order flow will be

$$\tilde{w} = \sum_{i=1}^{N} x_i + \left(\frac{\overline{\lambda}-\lambda}{\overline{\lambda}}\right)\tilde{y} + \tilde{z} \tag{A14}$$

In (A14), DLT's react to the price sensitivity from the market maker, since they know there will be an upcoming announcement and they are keen to the movement of the price in the market. So, when the price sensitivity is zero, they will take part in the market as they do before an unscheduled announcement. However, as the price sensitivity increases, they will participate in the market less and less. When the price sensitivity is the same as that of the bench mark case (i.e. the highest possible price sensitivity in the market), all DLT's will escape from the market.

With order flow information as in (A14), the market maker will decide the price as in (A15)

$$P(\tilde{\Omega}) = E[\tilde{F}] + \lambda\tilde{w} = E[\tilde{F} \mid \tilde{w}] = \overline{F} + \frac{Cov[\tilde{\delta}, \tilde{w}]}{Var[\tilde{w}]}\tilde{w} \qquad \text{(A15)}$$

So, the price sensitivity of order flow (λ) will be decided by covariance of dividend in the future and order flow and variance of order flow.

$$\lambda^S = \frac{N\beta Var[\tilde{\delta}]}{N^2\beta^2(Var[\tilde{\delta}] + Var[\tilde{\varepsilon}]) + \left(\frac{\overline{\lambda} + \lambda}{\overline{\lambda}}\right)^2 Var[\tilde{y}] + Var[\tilde{z}]} \qquad \text{(A16)}$$

With (A5) and (A16), the unique and positive price sensitivity of order flow (λ) is found in a fourth order equation as (A10) with reasonable values of parameters (i.e. $Var[\tilde{y}] \leq 8 \cdot Var[\tilde{z}]$).

$$\lambda^S = \overline{\lambda} = \frac{Var[\tilde{\delta}]}{(N+1)}\sqrt{\frac{N}{(Var[\tilde{\delta}] + Var[\tilde{\varepsilon}])Var[\tilde{z}]}} \qquad \text{(A17)}$$

Once the price sensitivity to order flow (λ) for an unscheduled announcement case is found, the trading aggressiveness of informed traders (β) will be as in (A11).

$$\beta^S = \underline{\beta} = \sqrt{\frac{Var[\tilde{z}]}{N(Var[\tilde{\delta}] + Var[\tilde{\varepsilon}])}} \qquad \text{(A18)}$$

Q.E.D.

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