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Trading Volume, Information Asymmetry, and Timing Information

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ABSTRACT

This paper investigates trading volume before scheduled and unscheduled corporate announcements to explore how traders respond to private information. I show that cumulative trading volume decreases inversely to information asymmetry prior to scheduled announcements, while the opposite relation holds for volume after the announcement. In contrast, trading volume before unscheduled announcements increases dramatically and shows little relation to proxies for information asymmetry. I investigate the behavior of market makers and find that they act appropriately by increasing price sensitivity before all announcements, implying that they extract timing information from their order books.

TRADING VOLUME PLAYS a critical role in financial markets. It facilitates the price discovery process, enables investors to share financial risks, and ensures that corporations can raise funds needed for investment. Trading volume is generally characterized as either informed or uninformed (liquidity trading). Although both types of trading volume are studied in the finance literature,[1] their relative importance remains poorly understood. In this paper, I study trading volume prior to important corporate announcements, when information asymmetry[2] is likely to be the greatest. The analysis provides insights into how informed and liquidity traders, along with market makers, respond to asymmetric information in the market.

Finance theory provides ambiguous predictions about trading volume prior to corporate announcements. When liquidity trading is exogenous and inelastic to price, as in Kyle (1985), trading volume increases in information asymmetry. This is because informed traders attempt to exploit their private information. However, if liquidity traders have timing discretion, as in Admati

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[1] See Karpoff (1987) or Lo and Wang (2000) for general references.

[2] Generally, information asymmetry may refer to asymmetric information or differential information between different agents. In this article, I use information asymmetry to mean that informed investors have material, firm-specific information related to future public announcements and that uninformed investors do not.

and Pfleiderer (1988) or in Foster and Viswanathan (1990), trading volume can decrease in information asymmetry. In these models, when discretionary liquidity traders (DLTs) receive exogenous trade demands prior to announcements, they will postpone trading until the announcement is made and the information asymmetry is resolved. Therefore, total volume can decrease before announcements and correspondingly increase afterwards. While theoretical models offer ambiguous predictions, little empirical evidence exists to distinguish between the predictions. In this article I offer such evidence.

I consider trading volume before two types of announcements: with and without timing information. Timing information refers to the public availability of when an announcement will be issued, and I designate these as scheduled announcements. When timing information is available, DLTs know that a large flow of information will be released on a specific date. Although they do not know what the information is, they can still optimize the timing of their trades to minimize adverse selection costs related to the information release. When timing information is not available, DLTs might not change the timing of their trades. I designate these as unscheduled announcements.

In this article, I use earnings announcements as scheduled announcements. Earnings announcements involve a release of information in which the timing is publicly known. Even though "pre" earnings announcements have become increasingly popular, the actual earnings announcement still resolves much uncertainty related to stock pricing. For unscheduled announcements, I use acquisition, target, and Moody's bond rating announcements. Neither the timing nor the magnitude and direction of these announcements is public information. I choose these four types of announcements because they represent major corporate events that have substantial impacts on prices.[3]

The following empirical analysis explores four related hypotheses to study trading dynamics around these announcements. Hypothesis 1 states that trading volume should decrease before scheduled announcements. The test compares abnormal trading volume before scheduled and unscheduled announcements, and the main results confirm hypothesis 1. Cumulative trading volume decreases more than 15% before scheduled announcements, but steadily increases before unscheduled announcements. This implies that DLTs do change their behavior depending on the existence of timing information.

Hypothesis 2 states that over a cross section of stocks, decreases in trading volume before scheduled announcements should be correlated with the extent of information asymmetry. Moreover, no such relation needs to hold before unscheduled announcements. I test and confirm hypothesis 2 by regressing abnormal trading volume before each type of announcement on commonly used proxies for information asymmetry (company size, number of analysts, bid–ask spread, and industry dummies).

Hypothesis 3 states that information asymmetry before scheduled announcements should be positively correlated with abnormal trading volume after

[3] See Bamber (1987), Foster et al. (1984), Jensen and Ruback (1983), Jarrell and Poulsen (1989a), and Hand et al. (1992), etc.

the announcements. This hypothesis is from George, Kaul, and Nimalendran (1994). These authors propose a theoretical argument that high trading volume immediately after corporate announcements is a result of increased liquidity trading.[4] Once the announcement has been made, DLTs perceive lower adverse selection costs and are finally willing to submit their trade demands. Investigating the relation between information asymmetry and volume, but after scheduled announcements instead of before, I find that the hypothesis of George et al. holds for most specifications.

Hypothesis 4 states that market makers should increase price sensitivity only before scheduled announcements. Market makers are uninformed with respect to corporate information, so they should increase their price sensitivity when they perceive adverse selection costs. To test this, I estimate the Kyle (1985) lambda for each stock during different periods around the announcement. These tests confirm that price sensitivity increases before scheduled announcements. However, I find that price sensitivity increases even before unscheduled announcements. This suggests that market makers are able to extract and react to information related to timing.

The rest of the paper is organized as follows: In Section I, I formally state the four hypotheses; in Section II, I describe the data sets and test the main (first) hypothesis; in Section III, I test the remaining three hypotheses; in Section IV, I suggest possible implications of the results; and finally in Section V, I offer concluding remarks.

I. Hypotheses

Many event studies about corporate announcements, such as earnings and takeovers, indicate that a considerable amount of information is released around these announcements. These releases of information often spur large price changes. For example, the absolute daily price change on earnings announcement dates is about 56% higher than the average absolute price change on other days in the same month.[5] Therefore, there is likely to be severe information asymmetry between informed and uninformed investors immediately before such announcements.

As shown in Milgrom and Stokey (1982), Black (1986), and Wang (1994), if there is a higher possibility of trading with an informed counterparty, then uninformed traders will participate less in the market. In an extreme case with only one informed investor and one uninformed investor, the informed investor wants to trade the stock before the information is revealed. However, this is almost impossible, since the uninformed investor will not trade unless there are urgent liquidity needs. Therefore, one could predict the outcome of this scenario to be a decrease in trading volume prior to the announcement. A

[4] Kim and Verrecchia (1991) and Atiase and Bamber (1994) offer another explanation of increasing trading volume on/after corporate announcements. The considerations of these studies follow in Section III.

[5] This is 45%, 287%, and 18% more than average on acquisition announcement, target announcement, and Moody's rating change, respectively.

necessary condition for this prediction to hold is that the uninformed investor must perceive a high level of information asymmetry and attempts of trading by the informed trader. Typically, uninformed traders have difficulty in differentiating between informed and uninformed trades.[6] However, before scheduled announcements (such as an earnings announcement), uninformed investors expect high trading demand from informed investors and avoid unnecessary trading. In response, total trading volume before scheduled announcements should decrease. On the other hand, uninformed investors cannot predict informed trading patterns around unscheduled announcements, so in these cases they cannot change their own trading patterns accordingly. In these cases, informed traders increase trading demand while uninformed traders trade as usual; the increase in informed trading should drive total trading levels higher before unscheduled announcements.

HYPOTHESIS 1: *Before an information-revealing announcement, trading volume should decrease only if uninformed investors expect the announcement.*

According to hypothesis 1, uninformed investors should avoid trading when they perceive adverse selection to be high. Adverse selection costs depend on ex ante information asymmetry. Therefore, trading volume before scheduled announcements should be negatively correlated with ex ante information asymmetry measures. This relation should not hold before unscheduled announcements, because uninformed investors cannot decrease their trade in response to an event they do not know about.

HYPOTHESIS 2: *Trading volume before scheduled announcements is negatively correlated with levels of ex ante information asymmetry.*

If hypothesis 2 is true, then discretionary liquidity traders are timing their trades. The decrease in trading volume before scheduled announcements represents the amount of delayed trading. To the extent that they must eventually fulfill their trading needs, DLTs should make up for postponed trades at some point after the announcement passes, causing an increase in ex post trading volume. In other words, a high level of ex ante information asymmetry causes a large amount of delayed trading, which leads to an increase in ex post trading. The increase in ex post trading should be positively related to the level of ex ante information asymmetry. This prediction is based on George et al. (1994). They develop a model in which high trading volume on announcement days can be explained by the relatively lower adverse selection costs immediately after information announcements.

HYPOTHESIS 3: *If adverse selection costs drive trading volume down before announcements, there should be a corresponding increase in trading volume after those announcements. Therefore, the relation between trading volume and*

[6] For an effort to estimate the probability of informed trading, see Easley, Hvidkjaer, and O'Hara (2002).

information asymmetry should be negative before and positive after scheduled announcements.

Admati and Pfleiderer (1988) and Foster and Viswanathan (1990) argue that DLTs try to trade during periods when price sensitivity to order flow is low. This implies that when uninformed investors avoid trade (i.e., before scheduled announcements), price sensitivity to order flow is high.

HYPOTHESIS 4: *Price sensitivity to order flow will be higher before scheduled announcements than during "average" periods.*

II. Tests

A. Data and Description of Variables

This paper tests four types of corporate announcements: earnings, acquisition, target, and Moody's bond rating change announcements. These types of announcements have well-documented effects on return and trading volume, as shown in Bamber (1987), Bamber and Cheon (1995), Foster, Olsen, and Shevlin (1984), and Hand, Holthausen, and Leftwich (1992).

As Chordia, Roll, and Subrahmanyam (2001) mention, earnings announcements are among the best candidates for scheduled announcements involving a release of relevant pricing information. Accordingly, I use earnings announcements as proxies for scheduled announcements. Among unscheduled corporate announcements, acquisition and target announcements also have significant effects on return and trading volume. For the most part, I use acquisition and target announcements as proxies for unscheduled announcements. Pricing information generated outside the relevant firm may lead to less insider trading than information generated within the firm. Because both acquisition and target announcements are generated within the relevant firm, I also use a set of Moody's bond rating change announcements for unscheduled announcements to test externally generated pricing information and to check for any difference in effects.

I/B/E/S data from 1986 to 2000 are used for the earnings announcement sample. The number of analysts for each stock and reporting dates are extracted from the I/B/E/S summary files. The total number of earnings announcements during this period is 65,912, all from NYSE and AMEX companies.

Acquisition and target announcements for NYSE and AMEX stocks are collected from the SDC database compiled by Thomson Financial Securities Data. To match the I/B/E/S time period, only data between 1986 and 2000 are included in the study. The total number of acquisition and target announcements are 25,087 and 12,485, respectively.

The Moody's bond rating data are hand-collected from Moody's investor services. Because of time constraints in manually recording the data, this data set spans a much shorter period, from January 1997 to October 1998. However, the sample of 410 announcements (all from the NYSE and the AMEX)

Table I

Data Sets and Applied Filter

This table reports the number of observations in each sample after filters are applied. The earnings announcement data between 1986 and 2000 are extracted from the I/B/E/S database. The companies had to be in the NYSE and the AMEX. The acquisition and the target announcement data between 1986 and 2000 are from the SDC database. The Moody's bond rating change data between January 1997 and October 1998 are hand-collected from Moody's Bond Survey published by Moody's Investors Service. "# of obs. filter" means that at least 40 trading days before and 10 days after the announcement are required to be included. The third and fourth rows indicate the number of observations for companies existing in two announcement data sets. For example, "Same companies in earnings and target" means that the companies have at least one earnings announcement and one target announcement.

NYSE and AMEX	Earnings	Acquisition	Target	Moody's
Before # of obs. filter	65,912	25,087	12,485	410
After # of obs. filter	64,285	22,930	11,255	320
Same companies in earnings and acquisition	55,747	19,888	N/A	N/A
Same companies in earnings and target	51,130	N/A	8,430	N/A

is large enough to draw meaningful conclusions from an event study analysis perspective.

Center for Research in Security Prices (CRSP) daily data for all companies in the NYSE and the AMEX (again from 1986 to 2000) are combined with these four samples to obtain trading volume. Only observations that have at least 40 days of data before and 10 days of data after announcements are included in the sample.

To control for firm-specific characteristics and increase the power of the tests, I match the companies' earnings and takeover data in the robustness check section. After separating out the companies that exist in both the earnings and acquisition announcement samples, there remain 55,747 earnings announcements and 19,888 acquisition announcements. For companies included in both the earnings and the target announcement data sets, there are 51,130 earnings announcements and 8,430 target announcements. The Moody's sample is too small to match with other data sets and retain enough data points. Table I contains the number of observations after each filter is applied.

Among many candidate measures of trading volume, I choose log turnover for most of the empirical tests in this paper. Raw turnover is defined as trading volume divided by outstanding shares.[7] It corrects for the number of outstanding shares, while absolute volume measures do not; this provides a cleaner interpretation of the results. Table II provides summary statistics on daily return, daily turnover, and log daily turnover from companies with at least 1 year of data between 1985 and 2000. However, the raw turnover distribution has a very fat tail and extreme positive skewness, which may be problematic. See Table II for these summary statistics.

Compared with the cross-sectional average skewness and kurtosis of returns (1.049 and 23.407, respectively, from 1986 to 2000), turnover is much more

[7] See Lo and Wang (2000) for a systematic description of different measures of trading volume.

Table II

Summary Statistics

This table reports summary statistics of daily percentage return and percentage turnover from stocks existing in the NYSE or the AMEX for at least 1 year (252 days). The summary statistics are the averages of estimates (mean, standard deviation, skewness, and kurtosis) for each company. The daily turnover is defined as daily trading volume divided by outstanding shares.

Period	Mean	*SD*	Skewness	Kurtosis	No. of Firms
		Daily Return (%)			
1986–2000	0.056	3.290	1.049	23.407	5,982
1986–1990	0.040	3.068	0.620	18.875	3,031
1991–1995	0.075	3.038	0.685	12.215	3,823
1996–2000	0.045	3.046	0.904	17.209	4,406
		Daily Turnover (%)			
1986–2000	0.389	0.865	8.596	159.439	5,982
1986–1990	0.260	0.439	7.166	101.495	3,031
1991–1995	0.272	0.447	7.259	108.934	3,823
1996–2000	0.447	0.964	7.317	108.898	4,406
		Log Daily Turnover			
1986–2000	−2.007	1.075	−0.098	0.701	5,906
1986–1990	−2.221	1.053	−0.026	0.590	2,972
1991–1995	−2.160	1.033	−0.091	0.630	3,731
1996–2000	−1.825	0.975	−0.022	0.826	4,404

non-normal. The extreme skewness and kurtosis (8.596 and 159.439, respectively) show a clear break from normality, an assumption required for the statistical procedures of this research. Therefore, as recommended by Ajinkya and Jain (1989), I apply the log function to correct for this.[8] Once the logarithm is applied, skewness and kurtosis decrease to −0.098 and 0.701, respectively. This transformed measure of trading volume appears to be very close to normally distributed, so I use it throughout the paper for empirical tests. Unless otherwise noted, any reference to volume, trading volume, turnover, and so on, all refer to log turnover as defined in equation (1).

$$\text{Log Turnover}(\tau_{i,t}) = \text{Log}\left(\frac{\text{Trading Volume}_{i,t}}{\text{Outstanding}_{i,t}}\right) \tag{1}$$

$$\text{Abnormal Turnover}(\xi_{i,t}) = \tau_{i,t} - \bar{\tau}_i, \quad \text{where } \bar{\tau}_t = \frac{\sum_{t=-40}^{t=-11} \tau_{i,t}}{30}. \tag{2}$$

The difference between log turnover during the test period and the estimation period is the measure of abnormal trading volume near announcements, as in equation (2).

[8] In the robustness check section of this paper, the ordinary turnover is used to provide similar results.

B. Empirical Results

Using the variables described in the previous section, I report cross-sectional average abnormal turnover ($\xi_{i,t}$) from $t = -10$ to 10 in Table III. The level of abnormal turnover before earnings announcements is much lower than before other announcements. In fact, trading volume before earnings announcements actually decreases significantly in the period from $t = -10$ to $t = -3$ with less than a 1% p-value. On average, I find a decrease of around 1–3% of daily trading volume prior to earnings announcements. For a summary measure, I construct the average abnormal turnover ($\sum_{t=-10}^{t=-3} \xi_{i,t}/8$) in the period from $t = -10$ to $t = -3$ and observe that the negative turnover is economically and statistically

Table III

Daily Abnormal Turnover around Different Events

This table contains the daily abnormal turnover around different types of announcements from the companies in the NYSE and the AMEX between 1986 and 2000. The abnormal turnover is reported as the difference between log turnover and average log turnover estimated from $t = -40$ to $t = -11$, where turnover is trading volume divided by shares outstanding. The t-statistics are given in parentheses to the right of their corresponding figures. Average(−10,−3) is the average abnormal turnover from $t = -10$ to $t = -3$. "Difference of averages from earnings" is the difference in Average (−10,−3) values from the earnings Average(−10,−3). The t-statistics are estimated with the assumption that the abnormal turnover for each announcement type has a different variance.

Announcements No. of Obs.	Earning 64,285	Acquisition 22,930	Target 11,255	Moody's 330
−10	−1.032 (−3.048)	2.044 (3.578)	9.342 (9.941)	2.842 (0.670)
−9	−1.852 (−5.367)	2.633 (4.524)	8.942 (9.363)	−1.929 (−0.443)
−8	−2.616 (−7.526)	2.239 (3.843)	11.727 (11.979)	−0.449 (−0.100)
−7	−2.645 (−7.573)	2.937 (4.963)	14.954 (14.885)	2.907 (0.696)
−6	−2.283 (−6.502)	3.538 (5.933)	16.345 (16.367)	3.657 (0.847)
−5	−1.418 (−4.083)	2.359 (3.974)	16.243 (16.165)	−0.529 (−0.115)
−4	−1.831 (−5.222)	4.073 (6.749)	17.955 (17.759)	2.050 (0.428)
−3	−1.381 (−3.910)	4.149 (6.839)	21.516 (21.092)	9.114 (1.730)
−2	0.863 (2.435)	5.819 (9.535)	26.733 (25.304)	13.693 (2.630)
−1	12.593 (34.627)	12.386 (19.852)	38.659 (34.851)	6.546 (1.138)
0	41.141 (108.997)	33.022 (49.506)	98.625 (75.857)	5.401 (0.939)
1	37.636 (100.763)	28.896 (43.922)	90.169 (71.989)	10.685 (1.880)
2	22.422 (61.530)	19.270 (30.746)	62.520 (54.358)	8.698 (1.542)
3	16.836 (46.624)	14.697 (23.650)	49.347 (44.044)	8.808 (1.632)
4	12.584 (34.918)	10.589 (16.976)	38.723 (35.956)	4.895 (0.941)
5	11.127 (30.726)	9.322 (15.035)	35.012 (32.120)	2.233 (0.480)
6	8.282 (22.848)	8.566 (13.996)	30.179 (28.603)	3.565 (0.710)
7	6.535 (18.003)	7.226 (11.642)	25.887 (24.447)	−1.765 (−0.356)
8	4.761 (13.058)	5.437 (8.809)	23.424 (22.183)	−1.005 (−0.204)
9	4.777 (13.180)	4.476 (7.259)	21.681 (20.475)	2.531 (0.521)
10	4.432 (12.066)	4.921 (7.978)	19.733 (18.853)	−7.742 (−1.555)
Average (−10,−3)	−1.882 (−8.955)	2.997 (10.231)	14.628 (9.497)	2.208 (1.820)
Difference of averages from earnings	N/A	4.879 (13.534)	16.510 (10.620)	4.090 (3.323)

significant (more than 15% cumulatively) with a t-statistic of -8.96.[9] Lower than average turnover on any day around information-revealing announcements is significant, but the continuous streak of low turnover days in this period is extraordinary.

I compare the results from scheduled earnings announcements with the results from the three types of unscheduled announcements in the last row of Table III.[10] This comparison will indicate that timing information is critical in trading volume dynamics before announcements. The time series pattern of turnover before unscheduled announcements exhibits clear differences from the pattern before scheduled (earnings) announcements. Instead of the negative abnormal trading volume seen before scheduled announcements, I observe positive abnormal trading volume prior to unscheduled announcements.[11] This is particularly conspicuous because of the sign change and the statistical significance of the differences.

As a graphical summary of these results, I provide plots of cumulative abnormal turnover in the period from $t = -15$ to $t = 15$ in Figure 1. Cumulative abnormal trading volume is calculated relative to the benchmark average log turnover, which is measured from $t = -45$ to $t = -16$. I intentionally use different estimation and testing periods to assure the robustness of the original results. Cumulative turnover before earnings announcements decreases for 12 consecutive days, by over 15% (Figure 1a). For all unscheduled announcements, instead of a decrease in cumulative abnormal turnover, there is a considerable increase.

To confirm that this measure of abnormal turnover is unbiased, I randomly select dates and companies and run the exact same procedure as for the announcements. I select days such that the estimation and the event window do not include any of the four types of previously tested announcements. As expected, the average abnormal turnover for these benchmark points is very near-zero for the period (Figure 1e). The flat, near-zero line in Figure 1e confirms that the measure of abnormal turnover is unbiased.

C. Robustness Check

For the analysis of daily abnormal turnover (in Table III), the estimation window is from $t = -40$ to $t = -11$ days. The first robustness check uses estimation windows of different lengths. I attach a summary table in Panel A of Table IV using an estimation window from $t = -55$ to $t = -11$. In this table, the main

[9] The number of days used in this summary measure (8) does not affect the relative size of turnover before earnings announcements compared to that before other announcements.

[10] Because the four different types of announcements (earnings, acquisition, target, and Moody's announcements) do not represent all corporate events, I implement a supplemental analysis with randomly selected events, which are simply days with high absolute return. Trading volume always increases before these events, and this pattern holds across various levels of high absolute returns. Detailed results are available from the author upon request.

[11] For an explanation of this positive abnormal trading volume, see Sanders and Zdanowicz (1992) or Jarrell and Poulsen (1989b).

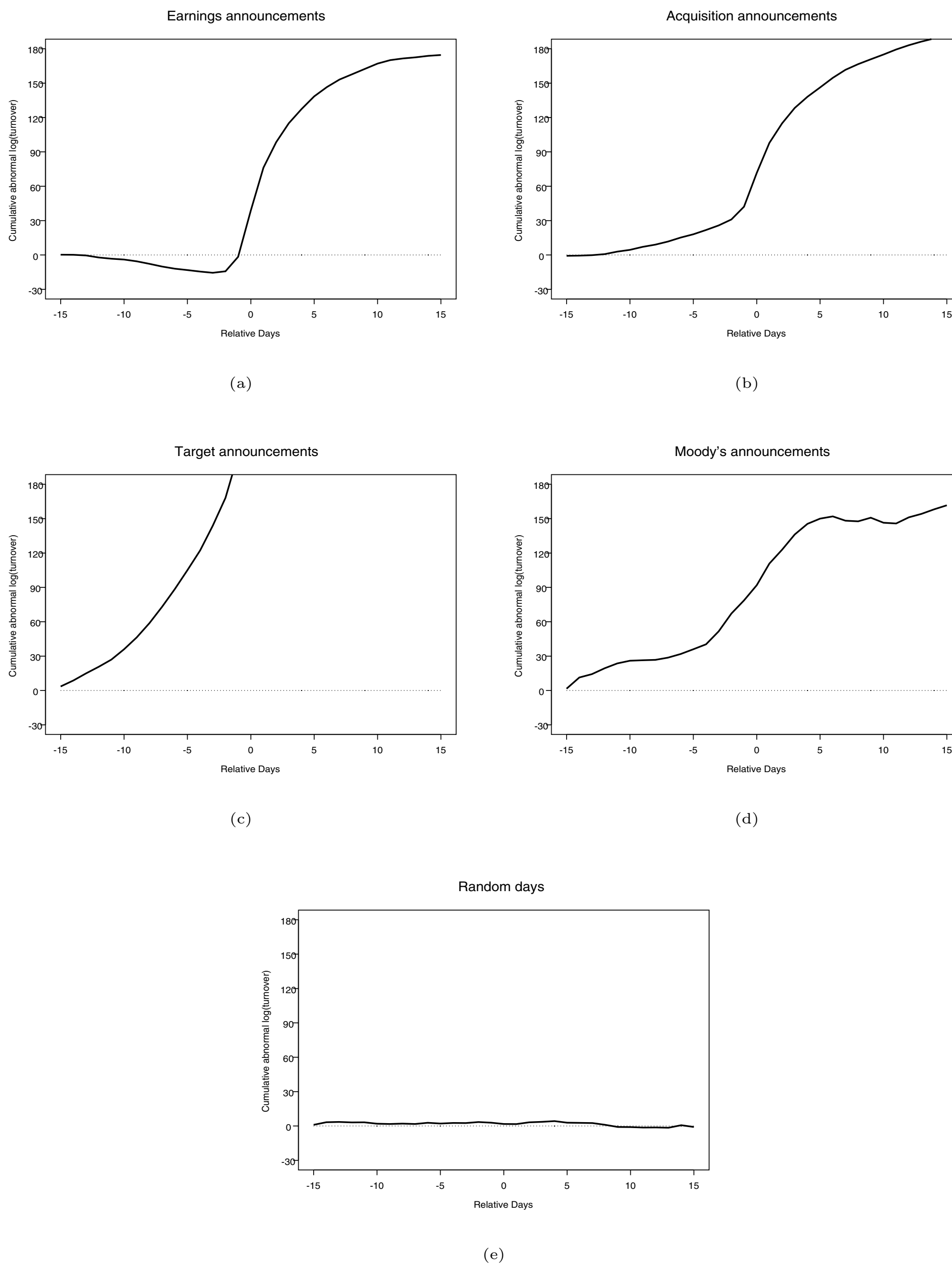

Figure 1. Cumulative abnormal log turnover from $t = -15$ to $t = 15$. For each announcement, the benchmark average log turnover is determined from $t = -45$ to $t = -16$ days, where turnover is daily volume divided by shares outstanding. These plots show cumulative abnormal turnover from $t = -15$ to $+15$, that is, the cumulative excess over the benchmark. Plot (e) selects random days as $t = 0$ and illustrates that the measure, cumulative abnormal turnover, is unbiased. For further explanation see Section II.

Table IV

Robustness Check

This table reports alternative measures of abnormal log turnover. Panel A employs a larger estimation window of 45 days, Panel B uses the difference between raw and median turnover, Panel C uses the residuals from a one factor market model, Panel D uses subperiod analysis, and Panel E uses matched samples. The rows of (−10, −3) and (3, 10) report the summary measures of average daily abnormal trading volume in the respective 8 days. Turnover is trading volume divided by shares outstanding. In Panels A, C, D, and E: $\diamond$, $\dagger$, and $\ddagger$ mean 10%, 5%, and 1%, respectively, in the left tail of t-distribution; $\circ$, $*$, and $\star$ mean 10%, 5%, and 1%, respectively, in the right tail of the t-distribution. In Panel B, $\diamond$, $\dagger$, $\ddagger$, $\circ$, $*$, and $\star$ are from a bootstrapped distribution.

Panel A: Using Larger Estimation Window ($t = -55$ to -11)

Announcement	Earnings	Acquisition	Target	Moody's
No. of Obs.	65,447	22,797	11,220	328
(−10, −3)	$-2.251^{\ddagger}$	$3.238^{\star}$	$16.115^{\star}$	5.170°
−2	0.506	$6.033^{\star}$	$28.179^{\star}$	$17.339^{\star}$
−1	$12.197^{\star}$	$12.598^{\star}$	$40.137^{\star}$	8.877°
0	$40.834^{\star}$	$33.290^{\star}$	$100.281^{\star}$	8.756°
1	$37.435^{\star}$	$29.099^{\star}$	$91.718^{\star}$	$14.073^{\star}$
2	$22.258^{\star}$	$19.524^{\star}$	$63.999^{\star}$	11.095^{*}
(3, 10)	$8.392^{\star}$	$8.427^{\star}$	$31.993^{\star}$	4.562

Panel B: Using Median Abnormal Turnover

Announcement	Earnings	Acquisition	Target	Moody's
No. of Obs.	64,014	22,817	11,162	330
(−10, −3)	$-2.492^{\ddagger}$	$1.177^{\star}$	$10.697^{\star}$	−1.482
−2	−0.236	$2.801^{\star}$	$21.460^{\star}$	6.885
−1	$11.666^{\star}$	$9.201^{\star}$	$33.547^{\star}$	−1.173
0	$46.212^{\star}$	$26.733^{\star}$	$116.091^{\star}$	−2.868
1	$41.153^{\star}$	$24.433^{\star}$	$103.052^{\star}$	10.164
2	$22.337^{\star}$	$13.962^{\star}$	$63.526^{\star}$	5.645
(3, 10)	$7.571^{\star}$	$5.908^{\star}$	$27.570^{\star}$	−0.200

(*continued*)

Table IV—*Continued*

Panel C: Using One-Factor Market Model

Announcement	Earnings	Acquisition	Target	Moody's
No. of Obs.	64,840	22,420	10,829	323
(−10, −3)	−4.186‡	2.265⋆	12.676⋆	2.028
−2	−2.333‡	4.187⋆	23.261⋆	13.186⋆
−1	9.076⋆	10.431⋆	35.452⋆	10.800*
0	36.989⋆	29.784⋆	93.230⋆	10.650*
1	33.600⋆	26.025⋆	85.358⋆	18.012⋆
2	19.875⋆	16.729⋆	59.024⋆	10.681*
(3, 10)	7.272⋆	7.306⋆	29.656⋆	1.137

Panel D: Using Subperiod

Announcement	Earnings			Acquisition			Target		
Subperiod	1986–1990	1991–1995	1996–2000	1986–1990	1991–1995	1996–2000	1986–1990	1991–1995	1996–2000
No. of Obs.	12,974	18,961	32,350	4,565	6,031	12,334	3,726	2,891	4,638
(−10, −3)	−0.821†	−2.807‡	−1.765‡	5.458⋆	2.063⋆	2.542⋆	21.247⋆	11.258⋆	11.413⋆
−2	7.237⋆	−0.533	−0.876†	10.009⋆	6.133⋆	4.115⋆	36.589⋆	21.478⋆	22.091⋆
−1	25.557⋆	8.337⋆	9.889⋆	14.899⋆	8.148⋆	13.529⋆	42.441⋆	23.985⋆	44.768⋆
0	31.024⋆	48.136⋆	41.098⋆	38.952⋆	34.209⋆	30.247⋆	113.681⋆	80.930⋆	97.560⋆
1	20.489⋆	42.777⋆	41.499⋆	33.651⋆	28.486⋆	27.337⋆	105.052⋆	72.592⋆	89.171⋆
2	11.487⋆	23.940⋆	25.918⋆	21.620⋆	18.277⋆	18.887⋆	72.479⋆	47.007⋆	64.184⋆
(3, 10)	6.512⋆	8.168⋆	9.823⋆	8.807⋆	6.302⋆	8.819⋆	34.527⋆	20.892⋆	33.250⋆

Panel E: From the Same Companies

	Companies in Both Earnings and Acquisition		Companies in Both Earnings and Target	
Announcements	Earnings	Acquisition	Earnings	Target
No. of Obs.	55,747	19,889	51,130	8,430
(−10, −3)	−1.915‡	2.908⋆	−1.887‡	12.228⋆
−2	0.723*	5.334⋆	0.609°	22.553⋆
−1	12.985⋆	11.749⋆	12.949⋆	34.813⋆
0	41.702⋆	31.228⋆	41.459⋆	86.962⋆
1	37.972⋆	27.916⋆	37.749⋆	76.786⋆
2	22.759⋆	18.134⋆	22.482⋆	51.983⋆
(3, 10)	8.712⋆	7.844⋆	8.826⋆	24.835⋆

result is even stronger than in Table III; cumulative abnormal turnover decreases more than 18% over 8 days. For brevity, I do not report the results from longer estimation windows. However, all tests with the estimation windows of up to one full year show similar results.

A second robustness check uses raw turnover instead of log turnover. In Panel B of Table IV, I use median abnormal turnover and a bootstrapped distribution for significance tests. Using the median raw turnover between $t = -40$ and $t = -11$ as a benchmark, I again estimate abnormal turnover in the testing period from $t = -10$ to $t = +10$. I report the cross-sectional median of the abnormal turnover. For the significance tests, I use a nonparametric bootstrapped distribution.[12] Once again, trading volume decreases significantly only before earnings announcements.

In an event study, abnormal levels of a variable (e.g., return or volume) are usually measured in one of two ways: using a fixed mean from an estimation period or using a market factor model. To investigate the robustness across both methods of defining abnormal turnover, I use a one-factor market model. I estimate the coefficient of a value-weighted log turnover index from the estimation period ($t = -40$ to $t = -11$), and apply this to obtain abnormal turnover in the testing period. The values, as reported in Panel C of Table IV, are the differences between the testing period and the estimation period log turnover, as shown in equation (3). As in the other robustness checks, a statistically significant decrease in turnover is observed only before earnings announcements. The cumulative difference from $t = -10$ and $t = -3$ using the market model is over 30%.

$$\text{Abnormal Tunrover}(\xi_{i,t}) = \tau_{i,t} - \hat{\alpha}_i - \hat{\beta}_i \tau_{m,t}. \tag{3}$$

To check stability over time, I provide subperiod results in Panel D of Table IV.[13] In all subperiods, I observe decreasing turnover only before earnings announcements. In the earliest of the three subperiods (1986 to 1990), the significance level is 5%. In the other two subperiods, cumulative abnormal turnover decreases by more than 15% and is much more significant.

Since I use several databases including different sets of companies, there might be unobservable company-specific characteristics in each database. I create two matched samples to control for firm-specific characteristics within each database, one matching earnings and acquisition companies and another matching earnings and target companies. For example, the earnings and acquisition matched sample includes only companies that exist in both the I/B/E/S earnings and the SDC acquisition databases. The results from the matched samples show an even stronger pattern of decreasing trading volume before earnings announcements (Panel E of Table IV). From the unmatched I/B/E/S

[12] The distribution for the cross-sectional median is constructed by generating 1,000 random samples with the same observation number as in the corresponding announcement data. See Efron and Tibshirani (1983) for a nonparametric bootstrap procedure.

[13] Because of the limited number of Moody's announcements, I cannot use these data in Panels D and E.

earnings database, I show that cumulative abnormal turnover from $t = -10$ to $t = -3$ is -15.06%. From the matched sample, the results are slightly stronger at -15.32% (acquisition matched) and -15.10% (target matched).

This series of robustness checks allows one to safely conclude that trading volume decreases significantly prior to scheduled earnings announcements and increases prior to unscheduled announcements.

III. Further Empirical Analysis

In this section, I test hypotheses 2, 3, and 4 to supplement the main results from hypothesis 1. First, testing hypothesis 2 will provide the cross-sectional relation between trading volume and information asymmetry. Next, testing hypothesis 3 will verify the theoretical predictions of George et al. (1994) and reconfirm the main result of this paper. Finally, testing hypothesis 4 will reveal price sensitivity to order flow before scheduled and unscheduled announcements.

A. Information Asymmetry and Trading Volume before Announcements

I now turn to analyzing the cause for decreased trading volume prior to scheduled earnings announcements. The intuition from most theoretical models is that greater information asymmetry results in less trading. I regress abnormal trading volume on information asymmetry proxies and control variables. Abnormally low trading volume is strongest between $t = -10$ and $t = -3$, so I define the dependent variable as the cumulative abnormal trading volume over this period. Testing different periods (from $t = -10$ to $t = -2$, etc.) as the dependent variable yields similar results, though the analysis using $t = -10$ to $t = -3$ most clearly illustrates this relation. In a later section, analyses on trading volume from $t = -2$ to $t = +2$ and from $t = +3$ to $t = +10$ will complement the analysis in this section.

To account for clustered data and obtain a more conservative econometric result, I implement Fama and MacBeth (1973) type regressions. Since earnings announcements are quarterly, each cross-sectional Fama/MacBeth type regression is done by quarter. However, there is a large variation in the number of observations in each quarter, so the usual procedure of using simple time series averages of the coefficients will provide inefficient estimations. Therefore, I use weighted averages of the coefficients in quarterly cross-sectional regressions (Table V). The weight used is the number of observations in each quarter. The regression specification for each quarterly cross-sectional regression is

$$\xi_{i,q} = \alpha_q + \beta_q \mathrm{InfoAsym}_{i,q} + \gamma_q \mathrm{Risk0}_{i,q} + \delta_q \mathrm{PrcChg}_{i,q} + \varepsilon_{i,q}. \tag{4}$$

The notation $\xi_{i,q}$ is the average daily abnormal log turnover between $t = -10$ and $t = -3$ at quarter q for company i; $\mathrm{InfoAsym}_{i,q}$ is each proxy for information asymmetry at quarter q for company i; $\mathrm{Risk0}_{i,q}$ is a control variable for risk on the announcement day; and $\mathrm{PrcChg}_{i,q}$ is another control variable defined as

Table V
Regression Analysis

This table reports the results of regressing abnormal log turnover before announcements on proxies of ex ante information asymmetry. All results are from Fama and MacBeth (1973) type regressions. The coefficients are the time series averages of the coefficients from cross-sectional regressions from each quarter. The time series averages of the coefficients are obtained by weighting the number of observations used in the cross-sectional regressions. t-statistics, given in parentheses beneath their corresponding figures, are from standard errors of these time series weighted averages. The dependent variable is defined as the difference between average log turnover from $t = -10$ to $t = -3$ and average log turnover from $t = -11$ to $t = -40$. Among independent variables, "Labsret0" is the absolute return on the last announcement day. All the coefficients have been multiplied by a factor of 100. $\bar{R}^2$ means the average of the adjusted R-squares in each cross-sectional regression.

Independent Variables									
Intercept	Log Cap	Number of Analysts	Average Spread [−70,−41]	Agriculture Fishing Mining	Logging Paper Printing	Petroleum	Labsret0	Absolute Return [−10,−3]	$\bar{R}^2$
Panel A: Earnings Announcements									
−15.82	0.68								0.61
(−2.40)	(2.15)								
−45.10	1.80						−49.18	2129.14	7.45
(−7.35)	(6.04)						(−5.96)	(18.82)	
−3.73		0.30							0.37
(−3.72)		(3.55)							
−10.55		0.41					−56.09	2073.03	7.09
(−10.54)		(4.98)					(−6.40)	(18.08)	
−0.92			−21.35						0.15
(−0.85)			(−0.91)						
−1.01			−303.05				−20.98	2237.05	7.39
(−0.96)			(−11.99)				(−2.47)	(19.01)	
−2.02				0.93	1.28	3.51			0.12
(−2.31)				(0.77)	(1.33)	(2.04)			
−8.05				−0.17	2.27	4.96	−56.23	2066.29	6.79
(−8.64)				(−0.14)	(2.34)	(2.75)	(−6.60)	(18.50)	

(*continued*)

Table V—*Continued*

Independent Variables									
Intercept	Log Cap	Number of Analysts	Average Spread [−70,−41]	Agriculture Fishing Mining	Logging Paper Printing	Petroleum	Labsret0	Absolute Return [−10,−3]	$\bar{R}^2$
Panel B: Acquisition Announcements									
17.50	−0.71								0.42
(2.70)	(−2.39)								
−10.62	0.31						−57.61	2219.17	9.15
(−1.66)	(1.09)						(−3.48)	(20.03)	
3.81		−0.12							0.23
(2.91)		(−1.61)							
−3.19		−0.05					−69.41	2163.97	8.03
(−2.71)		(−0.67)					(−3.80)	(19.01)	
4.37			−37.04						0.34
(2.91)			(−0.89)						
3.96			−366.59				−28.14	2409.57	10.15
(2.73)			(−7.85)				(−1.67)	(20.38)	
3.17				0.14	0.06	0.51			−0.04
(3.45)				(0.09)	(0.04)	(0.20)			
−4.01				−1.46	0.12	2.24	−61.60	2218.51	8.81
(−4.14)				(−0.92)	(0.10)	(1.13)	(−3.66)	(20.35)	
Panel C: Target Announcements									
52.75	−1.93								0.62
(7.49)	(−5.31)								
−5.62	0.30						12.03	2362.72	13.92
(−0.63)	(0.71)						(0.77)	(15.98)	
14.32		−0.45							0.24
(8.74)		(−3.80)							
−1.07		−0.12					12.23	2586.73	13.27
(−0.55)		(−0.89)					(0.55)	(11.21)	
14.31			6.79						0.72
(7.36)			(0.15)						
10.23			−416.01				28.92	2582.77	15.15
(5.06)			(−7.40)				(1.85)	(17.44)	
14.78				−4.15	2.65	−6.19			−0.18
(12.73)				(−1.38)	(0.83)	(−1.61)			
0.97				−8.68	2.11	−2.50	7.71	2370.85	13.57
(0.69)				(−2.93)	(0.66)	(−0.73)	(0.52)	(16.63)	

the difference between average absolute return and average absolute value-weighted market index return from $t = -10$ and $t = -3$.

Because there is no direct measure for information asymmetry, I use several proxies (firm size, analyst coverage, average bid–ask spread, and industry dummies) for robustness. In this study, size is defined as the logarithm of the market capitalization; analyst coverage as the number of analysts for each company in the I/B/E/S database; average bid–ask spread as the average of percentage bid-ask spreads between $t = -70$ and $t = -41$; and industry dummies as the 13 different categories used in Lewellen (1999). Each proxy is widely used in accounting and finance literature and has been shown to have intuitive economic relations with information asymmetry.

The use of firm size as a proxy can be justified by referring to Atiase (1985), Freeman (1987), Bamber (1987), Llorente et al. (2002), etc. For example, Atiase (1985) argues and empirically verifies that the amount of private pre-disclosure information dissemination is an increasing function of firm size; hence larger firms will have less information asymmetry before announcements. Hypothesis 2 implies that the larger the ex ante information asymmetry, the less trading activity will occur before scheduled announcements, so we should observe a positive statistical relation between firm size and trading volume before scheduled announcements.

Hong, Lim, and Stein (2000) show that holding all else equal, the more analysts covering a company, the more firm-specific information will be produced and the faster that information will be transmitted. Given that more analysts imply less information asymmetry, hypothesis 2 predicts that we should observe a positive relation between the number of analysts and the trading volume before scheduled announcements.

Copeland and Galai (1983), Glosten and Milgrom (1985), Venkatesh and Chiang (1986), etc., show that market makers should widen their bid–ask spreads when they suspect a high level of information asymmetry. Since high bid–ask spreads are associated with high information asymmetry, hypothesis 2 implies that there should be a negative relation between bid–ask spread magnitudes and volume before scheduled announcements.

Because of the nature of each company's business, earnings announcements from companies in different industries release different amounts of new information. For example, earnings announcements from clothing companies release much more pricing information than do announcements from petroleum companies. The performance of oil companies depends heavily on the market price of oil, which is readily available public information. The performance of clothing companies is driven largely by retail sales, which are certainly not publicly available and are extremely difficult to predict.[14] We may therefore predict that trading volume before scheduled announcements should be relatively higher for

[14] This is one reason why the average price impact of oil company earnings announcements is much smaller than clothing company earnings announcements. In fact, the average absolute return on earnings announcement days in the oil industry is 1.32%, the lowest level among all 13 industry groups.

the oil industry than the clothing industry; that is, we should see a positive coefficient for the dummy variables of specific industries, such as oil, mineral, etc.

Since trading volume is obviously driven by factors other than the level of asymmetric information, we must control for the most relevant factor. Contemporaneous price change is intuitively the most important, since high absolute price changes are often associated with high volume. This intuition is confirmed in theoretical studies (e.g., Wang (1994)) that show that trading volume is highly correlated with contemporaneous price volatility. As a result, I include the absolute price change in the period between $t = -10$ and $t = -3$.

Additionally, various empirical results show that volatility increases around earnings announcements (e.g., Donders and Vorst (1996)), implying that changing risk levels might also help determine trading volume. In a world with no information asymmetry, changing the risk of a security would induce trading demand as long as agents have differential risk aversion. For example, if a utility company acquires a high-risk biotech company, highly risk-averse agents should supply shares to the market and less risk-averse agents should demand shares. This volume would be induced at least partially because of changing risk, even if prices remain unchanged.

Since there is no universally accepted risk measure, I choose the two measures most relevant for this regression. The first is a total volatility measure: the price change on an announcement day ($t = 0$). In principle, this is an ideal measure of risk caused by the announcement, but it has a clear endogeneity problem. Specifically, high turnover prior to an announcement could lead to a small price effect on the day of the announcement. To account for this endogeneity problem, I use the price change from the announcement prior to the current announcement. This measure is a particularly good proxy for the price change around the current earnings announcement because of the low variation between the performance in adjacent quarters.[15] The second is a systematic risk measure: the change in market beta between pre- and post-announcement periods. I define the change in beta as the percentage change from the pre-announcement period (i.e., $t = -70$ to $t = -1$) to the post-announcement period (i.e., $t = +1$ to $t = +70$). Since nonsynchronous trading in daily data may affect estimates of beta, I use the estimation method used in Dimson (1979).

Table V reports the results from the analysis with the first risk measure, absolute price change from the previous announcement. The results using the other control variable are very similar and available upon request.

Table V reports the results from the Fama and MacBeth (1973) type regressions of abnormal trading volume before announcements on proxies of ex ante information asymmetry. The reported coefficients are time series averages from cross-sectional regressions using quarterly data. The time series averages are weighted by the number of observations in each cross-sectional regression, and

[15] The correlation between the absolute price change of this quarter's earnings announcement and the previous quarter's is 23.9%.

t-statistics are calculated with the standard errors of these time-series weighted averages.

As expected, we only notice the hypothesized relation between information asymmetry and trading volume before earnings announcements (Table V). The coefficients of size are statistically significant across different specifications. With two control variables, the coefficient for size is 1.89 with a t-statistic of 6.37. Conversely, size does not seem positively related to trading volume before either of the unscheduled announcements. If we accept the argument that information asymmetry is greater for smaller companies, then these results imply that information asymmetry affects trading behavior only before scheduled announcements.

Since analysts post their forecasts in various public and private media outlets, individual investors can obtain this information more easily if there are more analysts. If investors cannot easily find information, they are more likely to be uninformed. As uninformed investors, they should consider potential adverse selection costs and trade less when high information asymmetry is predictable. As shown in Table V, trading volume before earnings announcements is positively related with the number of analysts covering the company (0.41 with a t-statistic of 4.98). However, there is almost no relation between the number of analysts and trading volume before acquisition or target announcements. This suggests that uninformed investors know about their disadvantage before scheduled announcements, but not before unscheduled announcements.

Market makers are also considered to be uninformed with respect to inside corporate information (e.g., Kyle (1985), Venkatesh and Chiang (1986), etc.). Since the bid–ask spread is the primary method by which market makers protect themselves against adverse selection, it is commonly used as a proxy for information asymmetry (e.g., Llorente et al. (2002)). Table V shows the results from the regression using average bid–ask spread as an information asymmetry proxy. The coefficient has a statistically significant value (-303.05 with a t-statistic of -11.99) in the earnings announcement sample. However, unlike the results from the last two proxies, the coefficient of average bid–ask spread is statistically significant even in the acquisition and target samples (-366.59 with a t-statistic of -7.85 and -416.01 with a t-statistic of -7.40, respectively). One interpretation of this result follows from Stoll (1989). Stoll argues that the bid-ask spread has three components: order-processing costs, inventory holding costs, and adverse selection costs. The relation between abnormal trading volume and any of these three components may drive the negative relation. For example, high trading before acquisition and target announcements can be negatively related to inventory holding costs in the bid–ask spread cross sectionally. In this case, even if trading volume is not related to information asymmetry, we would still observe a negative relation (Panels B and C of Table V).

I show the effect of information asymmetry on trading volume using industry dummy variables in Table V. Prior to earnings announcements from firms in raw material industries (such as petroleum, logging, or mining), all traders have access to publicly available raw materials prices. Uninformed investors do not worry as much about their information disadvantage because most

Table VI

Wald Test: Comparison of Coefficients before Different Announcements

This table implements the Wald test to compare the coefficients of information asymmetry proxies for scheduled earnings announcements to those for unscheduled announcements. The 95% significance level for Chi-square with degree of freedom = 1 is 3.84.

Log Cap	Number of Analysts	Average Spread [−70, −41]	Agriculture Fishing Mining	Logging Paper Printing	Petroleum
Panel A: Comparison between Earnings and Acquisition					
13.04	17.44	1.43	0.40	1.98	1.03
Panel B: Comparison between Earnings and Target					
8.43	11.36	3.36	6.99	0.00	3.73

relevant pricing information is public. Corporate announcements have a relatively low price impact in these industries, so they can continue to trade before scheduled earnings announcements. Again, statistically significant positive coefficients for our raw materials groupings (e.g., 4.96 with a t-statistic of 2.75 for the oil industry dummy) are observed only for scheduled earnings announcements.

To test the statistical differences between regression coefficients for scheduled earnings announcements and unscheduled announcements, I implement the Wald test. Table VI reports the results. Most of the information asymmetry proxies in the unscheduled announcements sample are statistically different from the proxies in the scheduled earnings announcements sample. For example, the Wald statistic for the size coefficients from earnings and acquisition announcements is 13.04 with a p-value of 0.0006. This provides evidence that information asymmetry influences trading volume before unscheduled announcements in a very different way than before scheduled announcements. Without timing information, uninformed investors do not seem able to realize high information asymmetry, and thus do not optimize their trading.

B. Information Asymmetry and Trading Volume on/after Announcements[16]

In the previous section, I tested the relation between trading volume before scheduled earnings announcements and ex ante information asymmetry. In this section, I analyze trading volume on and after earnings announcements (as in hypothesis 3).

Explanations about trading volume patterns on and after public announcements may be found in Kim and Verrecchia (1991) and Atiase and Bamber

[16] I am indebted to anonymous referees for revisions to this section.

(1994). Kim and Verrecchia build a model of trading volume in which public announcements are positively related to the price change and the degree of pre-disclosure information asymmetry. Following this theoretical prediction, Atiase and Bamber provide empirical evidence that trading volume increases on annual earnings announcements dates. According to these two papers, pre-disclosure information asymmetry causes differential pre-disclosure expectations. Upon public announcements, the revision of these expectations generates abnormally high trading volume.

On the other hand, George et al. (1994) argue that the increase in trading volume on announcements can be explained by lower adverse selection costs after announcements. Though George et al. do not directly state that trading volume should decrease before announcements (when adverse selection costs are still high), such a pattern follows as a reasonable extension of their argument. Though I verified this extension in previous sections, a more direct test of their prediction would determine whether the relation between trading volume and information asymmetry reverses from before to on/after announcements. Any negative abnormal trades that are delayed before scheduled announcements should be submitted after the announcement. Evidence from this test will reconfirm the results in previous sections.

These two explanations for high trading volume on/after public announcements are different in their specific reasoning, but both originate from pre-disclosure information asymmetry. Both predict that trading volume on/after announcements should be positively correlated with the level of pre-disclosure information asymmetry. Based on this prediction and on hypothesis 3, I report the relation between trading volume on/after earnings announcements and the level of pre-disclosure information asymmetry in Table VII.

The regressions in this section have the same specifications as in the last section, except that the dependent variable is now abnormal turnover on and after (instead of before) announcements (see Table VII). The dependent variable in Panel A is abnormal turnover on an earnings announcement (from $t = -2$ to $t = +2$), and the dependent variable in Panel B is abnormal turnover after an earnings announcement (from $t = +3$ to $t = +10$). As in hypothesis 3, the coefficients for information asymmetry proxies change sign (or at least are much smaller in magnitude) when comparing regressions of ex post volume to ex ante volume. For example, the coefficient for firm size (log cap) changes from 0.68 in Panel A of Table V to -1.66 in Panel A of Table VII. This change in sign means that the negative relation between trading volume before earnings announcements and ex ante information asymmetry has reversed into a positive relation between trading volume on/after earnings announcements and ex ante information asymmetry.

In Table VIII, I also implement the Wald test to see how statistically different the coefficients are. Most coefficients for information asymmetry proxies are significantly different. The Wald statistics are much larger than 3.84, which is the critical value of 95% in the Chi-square distribution. Generally, these results confirm the predictions of Kim and Verrecchia (1991), George et al. (1994), and hypothesis 3. In summary, the level of ex ante information asymmetry appears

Table VII

Regression Analysis

This table reports the results of regressing abnormal log turnover during and after earnings announcements on proxies of ex ante information asymmetry. All results are from Fama and MacBeth (1973) type regressions. The coefficients are the time series averages of the coefficients from cross-sectional regressions from each quarter data. The time-series averages of the coefficients are obtained by weighting the number of observations used in the cross-sectional regressions. The t-statistics, appearing in parentheses beneath their corresponding figures, are from standard errors of these time-series weighted averages. The dependent variables are defined as the difference between average log turnover from $t = -2$ to $t = +2$ and average log turnover from $t = -40$ to $t = -11$ for Panel A, and the difference between average log turnover from $t = +3$ to $t = +10$ and average log turnover from $t = -40$ to $t = -11$. Among independent variables, "Labsret0" is the absolute return on the last announcement day. All the coefficients have been multiplied by a factor of 100.

Independent Variables									
Intercept	Log Cap	Number of Analysts	Average Spread [−70, −41]	Agriculture Fishing Mining	Logging Paper Printing	Petroleum	Labsret0	Absolute Return [−10, −3]	$\bar{R}^2$
Panel A: On Earnings Announcements [−2, +2]									
56.83	−1.66								0.86
(5.99)	(−3.72)								
7.01	0.07						25.62	1968.77	12.62
(0.89)	(0.19)						(2.38)	(21.66)	
23.24		−0.03							0.27
(15.33)		(−0.32)							
7.84		0.11					26.07	1960.61	12.30
(5.32)		(1.16)					(2.36)	(20.98)	
21.50			72.10						0.29
(13.32)			(1.88)						
17.10			−386.79				74.99	2082.33	12.92
(11.12)			(−13.20)				(6.88)	(21.71)	
23.50				−6.51	−0.52	−9.41			0.23
(18.17)				(−4.15)	(−0.43)	(−3.37)			
8.78				−6.48	1.80	−4.66	26.49	1973.44	12.30
(6.45)				(−4.32)	(1.56)	(−1.75)	(2.34)	(21.19)	

Panel B: After Announcements [+3, +10]

23.89	−0.74								0.89
(2.52)	(−1.68)								
−5.20	0.38						−51.47	2157.79	6.55
(−0.58)	(0.91)						(−4.31)	(17.44)	
9.91		−0.18							0.43
(5.73)		(−1.65)							
2.93		−0.04					−53.80	2120.67	6.94
(1.64)		(−0.37)					(−4.58)	(17.12)	
14.38			−203.61						0.52
(7.90)			(−5.94)						
13.63			−497.35				9.89	2401.45	7.29
(7.76)			(−14.42)				(0.84)	(18.76)	
8.89				−2.82	1.56	−5.33			0.25
(6.13)				(−1.66)	(1.33)	(−2.09)			
2.70				−3.65	2.43	−4.11	−52.55	2146.21	6.09
(1.74)				(−2.12)	(2.06)	(−1.68)	(−4.42)	(16.88)	

Table VIII

Wald Test: Comparison of Coefficients

This table implements the Wald test to compare the coefficients of information asymmetry proxies for earnings announcements with different dependent variables. Panel A compares the multivariate Fama/MacBeth type coefficients of information asymmetry proxies for log turnover prior to earnings announcements ($t = [-10, -3]$) and those on earnings announcements ($t = [-2, +2]$). In Panel B, it compares the multivariate Fama/MacBeth type coefficients of information asymmetry proxies for log turnover prior to earnings announcements ($t = [-10, -3]$) and those after earnings announcements ($t = [+3, +10]$). The 95% significance level for Chi-square with degree of freedom = 1 is 3.84.

Log Cap	Number of Analysts	Average Spread [−70,−41]	Agriculture Fishing Mining	Logging Paper Printing	Petroleum
Panel A: Comparison with "On Earnings Announcements [−2, +2]"					
12.70	5.77	4.68	10.42	0.10	8.95
Panel B: Comparison with "After Earnings Announcements [+3, +10]"					
7.90	11.06	20.66	2.68	0.01	8.91

to drive the levels of abnormal turnover before and after scheduled earnings announcements in different directions.

C. Price Sensitivity of Market Makers

According to Kyle (1985), market makers should increase price sensitivity to order flow to protect themselves when they expect more informed trading. Therefore, by comparing price sensitivity near announcements to "average" periods, I should be able to make inferences about the level of information asymmetry that market makers perceive. As discussed in the previous sections, uninformed traders behave differently depending on the availability of timing information. Though they do not have inside information, market makers do have more information (order flow, order books, etc.) than uninformed investors. An analysis of their behavior should indicate how their information set affects their behavior around announcements with and without timing information.

I use the Trade and Quote (TAQ) database for these tests. First, 1,100 observations are randomly selected from each of the initial earnings, acquisition, and target data sets. After matching these with the TAQ database, there remain 1,068, 1,025, and 961 observations, respectively. Table IX reports price sensitivity to order flow across announcement types. The price sensitivity is measured by regressing return on signed order flow.[17] Since the number of trades is likely related to ex ante information asymmetry and informed/uninformed investors'

[17] The Lee and Ready (1991) tick test is used to determine the sign of each trade order.

Table IX

Abnormal Price Sensitivity before Announcements

Price sensitivity (λ) is estimated for the corresponding period, $t = -40$ to -11 or $t = -10$ to -3, in random samples from the initial data sets of earnings, acquisition, and target announcements. The numbers of observations in the initial data sets are 65,912 earnings announcements, 25,087 acquisition announcements, and 12,485 target announcements. From 1,100 randomly selected observations in each announcement data set, after matching with the Trade and Quote (TAQ) data set and applying a number of observation filters, the final data sets have 1,068 earnings, 1,025 acquisition, and 961 target observations. To estimate price sensitivity, I regress return (in basis points) on signed order flow (in hundreds, signed by the technique in Lee and Ready (1991)).

Average Number of Trading per day in $(-10, -3)$	(0, 10]	(10, 100]	$(100, \infty)$	Total
Panel A: Earnings Announcements				
$\lambda_{(-10,-3)} - \lambda_{(-40,-11)}$	1.018	0.228	0.017	0.255
t-statistics	(4.47)	(6.27)	(1.19)	(6.96)
No. of obs.	140	538	390	1,068
Panel B: Acquisition Announcements				
$\lambda_{(-10,-3)} - \lambda_{(-40,-11)}$	0.879	0.173	0.052	0.211
t-statistics	(3.26)	(4.25)	(1.59)	(5.12)
No. of obs.	126	486	413	1,025
Panel C: Target Announcements				
$\lambda_{(-10,-3)} - \lambda_{(-40,-11)}$	1.915	0.199	0.036	0.425
t-statistics	(5.04)	(5.06)	(3.46)	(6.22)
No. of obs.	156	491	314	961

trading in the market, I sort the companies in the data set by the total number of trades in the testing period. After obtaining price sensitivities from the estimation and testing periods, I construct a measure of the difference between these periods.

I find that market makers raise price sensitivity before all three types of announcements (see Table IX). Without any restriction on the number of trades in the testing period, the differences in price sensitivities between the testing and estimation period are 0.255, 0.211, and 0.425 from earnings announcements, acquisition announcements, and target announcements, respectively. All of these differences are statistically significant. Therefore, market makers increase price sensitivity before all announcements, whether scheduled or not.

This result warrants further investigation. First of all, market makers increase price sensitivity before scheduled announcements as expected. This can be explained with the same argument as before, namely, that market makers know informed traders are in the market and increase price sensitivity to protect themselves.

More interestingly, market makers also increase price sensitivity before unscheduled announcements. I propose the following explanation. Market makers have a special type of “non-inside but private” information in their order books. The order book may somehow reflect timing information or informed limit orders. If market makers can extract timing information or detect information-based limit order trading, they can optimize their behavior (increase price sensitivity) regardless of the existence of public timing information. This increased price sensitivity would not be observed by uninformed investors since order-by-order information is not instantly available.

Based on the results in this section, market makers generally behave in an appropriate way to protect themselves. They find and react to abnormal movements in order flow near announcements even without public timing information. Therefore, I conclude that decreased trading volume before earnings announcements is consistent with market makers’ price-setting behavior.

D. Annual, Quarterly, and Combined Earnings Announcements[18]

Recent empirical studies show that investors and analysts may have different levels of consensus in their posterior beliefs after different types of earnings announcements (annual, quarterly, and combined announcements). For example, if investors and/or analysts have heterogeneous prior beliefs about annual earnings forecasts, some of this heterogeneity should remain even after quarterly announcements. Only after the annual earnings announcements will the heterogeneity be resolved. If annual earning forecasts are relevant to pricing, then there should be differences in patterns of abnormal trading volume across these three types of announcements.

Panel A in Table X reports the daily abnormal turnover around all three types of earnings announcements. The rows labeled (−10, −3) and (3, 10) show the summary measures of average daily abnormal trading volume. Abnormal volume before quarterly announcements is negative, while abnormal volume before annual and combined earnings announcements is positive. This confirms that there are different volume patterns before quarterly announcements than there are before other announcements, but conclusions drawn from Panel A would be misleading without further analysis.

In Panel B, I estimate average abnormal turnover for subsamples of each type of announcement, splitting first quarter announcement from “rest-of-year” announcements. For all three types, abnormal trading volume is positive before first quarter announcements and negative before rest-of-year announcements. This pattern may be explained by again resorting to the information asymmetry hypothesis. Since most annual earnings announcements are issued in the first quarter of each year, we observe more analyst reports and media coverage of corporate news during the first quarter. Since investors have more information in the first quarter (or at least believe that more reporting is equivalent to better information), they do not adjust their trading patterns. During the rest of the year, the availability of information decreases and uninformed investors truly believe they are uninformed. Hence, they decrease trading before

[18] I thank the anonymous referees for their suggestion to do the analysis in this section.

Table X

Abnormal Trading Volume around Annual, Quarterly, and Combined Earnings Announcements

This table reports the daily abnormal turnover around annual, quarterly, and combined earnings announcements. The abnormal turnover (from companies in the NYSE and the AMEX between 1986 and 2000) is reported as the difference between log turnover and average log turnover (estimated from the benchmark period $t = -40$ to $t = -11$). The t-statistics are given in parentheses beneath their corresponding figures. The rows (−10, −3) and (3, 10) report the average of daily abnormal trading volume from $t = -10$ to $t = -3$ and from $t = 3$ to $t = 10$, respectively. Panel A reports full-year estimates of abnormal turnover around earnings announcements. Panel B splits the full-year sample into first quarter and rest-of-year subsamples.

Announcements	Annual Only	Quarterly Only	Combined
	Panel A: Full-Year Results		
From Months	1–12	1–12	1–12
No. of obs.	9,050	53,906	8,286
(−10, −3)	0.266	−2.367	2.199
	(0.456)	(−10.719)	(4.004)
−2	4.076	0.065	6.122
	(4.044)	(0.167)	(6.441)
−1	17.305	11.675	19.318
	(16.429)	(29.372)	(19.411)
0	34.167	39.875	49.383
	(32.175)	(96.651)	(48.230)
1	29.764	36.507	44.188
	(28.123)	(89.293)	(43.685)
2	21.237	21.324	29.393
	(20.410)	(53.535)	(29.770)
(3, 10)	8.893	7.768	14.896
	(13.401)	(30.608)	(23.869)

Announcements	Annual Only		Quarterly Only		Combined	
	Panel B: First Quarter vs. Other Quarter Results					
From Months	1–3	4–12	1–3	4–12	1–3	4–12
No. of Obs.	6,959	2,091	5,256	48,650	5,326	2,960
(−10, −3)	0.819	−1.573	1.642	−2.801	4.378	−1.723
	(1.315)	(−1.092)	(2.235)	(−12.102)	(6.532)	(−1.815)
−2	4.004	4.316	7.877	−0.779	8.230	2.330
	(3.698)	(1.755)	(6.118)	(−1.911)	(7.284)	(1.359)
−1	17.585	16.371	16.064	11.201	19.717	18.602
	(15.451)	(6.453)	(12.208)	(26.873)	(16.483)	(10.515)
0	34.765	32.179	52.807	38.478	48.080	51.727
	(30.483)	(12.415)	(38.865)	(88.975)	(39.464)	(28.021)
1	30.536	27.195	51.196	34.921	43.905	44.697
	(27.044)	(10.384)	(38.064)	(81.501)	(36.327)	(24.645)
2	22.571	16.797	30.922	20.287	28.687	30.662
	(20.334)	(6.526)	(23.964)	(48.476)	(24.194)	(17.450)
(3, 10)	9.656	6.354	16.757	6.797	16.178	12.590
	(13.479)	(3.970)	(19.659)	(25.616)	(21.460)	(11.447)

scheduled announcements during the rest of the year. By observing the number of observations of each type of announcement in the first quarter relative to the rest-of-year, we see that quarterly announcements are concentrated in the rest-of-year, while annual and combined announcements are concentrated in the first quarter. This explains the differences noted earlier between quarterly and annual/combined announcements.

IV. Other Implications

Based on the tests in this paper, I show that timing information alerts uninformed investors to evaluate adverse selection costs and optimize the timing of their trades. Without timing information, uninformed investors cannot react to potential adverse selection costs. Another interpretation of these results is that uninformed investors might be overconfident. As shown in takeover (and especially in target) announcements, uninformed investors maintain participation in the market day after day, even though abnormally high trading volume is publicly observable on a daily basis. Although they know that informed investors exist and that trading volume is high, uninformed investors do not consider possible adverse selection unless there is an explicit scheduled announcement. This phenomenon may be an example of the behavioral finance argument that investors are overconfident.

Another point to reflect upon is the behavior of market makers. Market makers are also uninformed about the timing of announcements. However, they react consistently whether or not there is timing information. I reason that private observation of their order books and of order flow can help them detect impending information issuances, and thereafter protect themselves by increasing the price sensitivity. Therefore, it would also be interesting to see if the same trading volume patterns exist when the order book and order flow are public information, such as on the Paris Bourse.[19] The results in this paper contribute to understanding potential effects of information disclosure in the stock market and optimal transparency of dealer-specific information.

V. Conclusion

Using I/B/E/S earnings announcement data, I find that cumulative trading volume decreases by more than 15% before scheduled earnings announcements. Before all investigated unscheduled announcements (SDC takeover, SDC target, and Moody's bond rating change), cumulative trading volume increases. I also show that cross sectionally, trading volume is negatively correlated with levels of information asymmetry *before* scheduled announcements and positively correlated with information asymmetry *after* scheduled announcements. Again, this pattern holds only for scheduled announcements.

All the results for scheduled announcements are consistent with theories of asymmetric information, in which DLTs decrease trading volume when they

[19] I appreciate Carl Hopman's help in providing information about the Paris Bourse.

perceive high adverse selection costs. However, I find that market makers act appropriately by increasing price sensitivity before all announcements, including unscheduled announcements. This may imply that market makers extract timing information from their order books. On the other hand, liquidity traders do not seem to correctly read information embedded in prices and volume before unscheduled announcements. This suggests that uninformed liquidity traders cannot behave according to theories of information asymmetry unless they have timing information.

These results leave two open questions. First, what is the relationship between timing information and return/volatility? Second, what makes market makers increase price sensitivity before all types of announcements? Studies of these questions will yield further advances in our understanding of trading under information asymmetry.

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