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Journal of Banking and Finance, 2013; 37:4134-4143

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9 September 2013

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The Relationship between the Frequency of News Release and the Information Asymmetry: The Role of Uninformed Trading

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Abstract

This paper shows that the degree of information asymmetry is lower for firms with more frequent news releases. The relation holds for various measures of information asymmetry such as the probability of information-based trading (*PIN*), permanent price impact, and adverse selection component of bid-ask spread, even after adjusting for endogeneity between news release and information asymmetry. By decomposing the *PIN* into intensities of uninformed and informed trades, similarly to Brown and Hillegeist [2007, Review of Accounting Studies 12, 443-477], we find that intensity of uninformed trading increases much more than that of informed trading for firms with more frequent news releases. As a result, information asymmetry, as is measured by *PIN*, decreases for such firms due to the large increase in the intensity of uninformed trading. Our findings highlight not only the importance of news releases in leveling the playing field of investors but also the role of uninformed investors in reducing trading cost due to information asymmetry.

Key Words: News release, Information asymmetry, *PIN*, Uninformed trading

JEL: G14, D82

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We are grateful for very helpful comments from participants of the 2007 China International Conference in Finance annual meeting, 2007 Financial Management Association annual meeting, 2007 Australian Finance and Banking annual conference, and finance seminars at the National University of Singapore and Concordia University.

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This paper shows that the degree of information asymmetry is lower for firms with more frequent news releases. The relation holds for various measures of information asymmetry such as the probability of information-based trading (*PIN*), permanent price impact, and adverse selection component of bid-ask spread, even after adjusting for endogeneity between news release and information asymmetry. By decomposing the *PIN* into intensities of uninformed and informed trades, similarly to Brown and Hillegeist [2007, Review of Accounting Studies 12, 443-477], we find that intensity of uninformed trading increases much more than that of informed trading for firms with more frequent news releases. As a result, information asymmetry, as is measured by *PIN*, decreases for such firms due to the large increase in the intensity of uninformed trading. Our findings highlight not only the importance of news releases in leveling the playing field of investors but also the role of uninformed investors in reducing trading cost due to information asymmetry.

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1. Introduction

".....The laws and rules that govern the securities industry in the United States derive from a simple and straightforward concept: all investors, whether large institutions or private individuals, should have access to certain basic facts about an investment prior to buying it, and so long as they hold it....." (SEC Mission Statement)

Market regulatory agencies tend to view regular disclosure of public information by managers as primary means of maintaining an orderly financial market, believing that such disclosure levels the playing field for all investors as it reduces the degree of information asymmetry among investors. For example, the US Securities Exchange Commission (hereafter, SEC) enacted Regulation Fair Disclosure (REG FD) which prohibits managers from making selective disclosures to specific investors without accompanying public disclosure of similar information to all investors.¹ However, existing research in finance and accounting that examines the degree of information asymmetry around news events shows that information asymmetry *increases* immediately before and after events such as earnings and dividend announcements. For example, Krinsky and Lee (1996) and Cong, Hoitash and Krishnan (2010) find that the degree of information asymmetry increases after earnings announcements. Koski and Michaley (2000) find similar results before dividend announcements. However, the results of these event studies might strongly reflect the short-term impact of trading by informed investors who react immediately to news events.² If uninformed investors do not react to information immediately with the same trading intensity as informed investors, it might take longer time for the impact of uninformed trading to materialize in

¹ The disclosure is done through SEC filing using Form 8K.

² In contrast with previous studies, a recent study by Amiram, Ownes and Rozenbaum (2012) show that analysts forecast announcements decrease information asymmetry around the announcement event.

market prices. Thus, a narrow window around event dates applied in these studies might not be able to capture the response of uninformed investors. To complement the prior event studies, our paper measures the levels of disclosure by the frequency of news release and relates them to the intensities of informed trading and uninformed trading. Thus, the resultant information asymmetry is measured over a time horizon longer than that in previous event studies. The primary goal of this paper is to reconcile the seemingly opposing implications of previous event studies by studying the cross sectional relation between the frequency of news release and the degree of information asymmetry which is measured over a longer time frame.

We test the above objective using a sample of 1031 firms whose common stocks were traded on the NYSE during the calendar year 2004. We measure the frequency of news release based on *all* firm-specific news appearing on www.MarketWatch.com. This website receives news stories from over 20 high profile financial news media that cover press releases by firms, SEC filings and other firm specific news. Such a broad coverage of news allows us to make general statements about the effect of news releases on the information asymmetry among investors, instead of focusing on a few specific news events such as earnings and dividend announcements. In this paper, we use the Probability of Information-based Trading, *PIN* (Easley et al. 1996), the decomposed bid ask spread (Huang and Stoll, 1997), and the permanent price impact of trades (Hasbrouck 1991) as measures of information asymmetry. However, we use the *PIN* for reporting our main results and present robustness test results for the other measures.

Prior literature posits that the frequency of news release and measures of information asymmetry could be endogenously determined. Coller and Yohn (1997)

suggest that managers release information to reduce information asymmetry in the stock market, where they find that management forecasts reduce information asymmetry. Brown and Hillegeist (2007) model an endogenous structure for the relation between earnings disclosure quality and information asymmetry.³ Similarly, news media are more likely to cover firms where information asymmetry is greater since the demand for news might be higher for these firms. In our tests, in addition to a single equation model, we also control for this endogenous relation between information asymmetry and the frequency of news release by using a 2SLS estimation model. We find that information asymmetry is lower for firms with more frequent news release, which is in contrast to the findings by previous event studies that show information asymmetry increases around public announcement events.⁴ Our results also support the finding in a recent study by Tetlock (2010) that examines the relations between public news and reversal of daily stock returns and volume-induced momentum, among other relations, and suggests public news releases mitigate information asymmetry.

We further explore the channel that leads to the negative relation between the frequency of public news release and information asymmetry. Although the trading of both informed and uninformed investors jointly determines the degree of information asymmetry of the market, both types of investors may have different incentives to rely on public information in forming their trading strategies. Previous studies of asymmetric information and investor trading have mostly focused on the strategic behavior of

³ Recent empirical works relating firms' information disclosure to the cost of capital treat disclosure as an endogenous choice variable; see, e.g., Leuz and Verrecchia (2000) and Cohen (2003).

⁴ Our cross-sectional finding does not necessarily contradict those in the event studies. Information asymmetry around news events may be affected more by the trading by informed investors with private interpretation of news (Kim and Verrecchia, 1994 and 1997), while information asymmetry measured over a long horizon may reflect more of uninformed trading as a result of more information being incorporated into prices.

informed investors. For example, Bagnoli and Watts (1998) show a model where informed traders gather private information in anticipation of a news release and take positions to profit from this information. They show that informed trading is more aggressive and prices become more informative around public news releases. Kim and Verrecchia (1994) present a model where information asymmetry increases instead after the news release as informed traders gather private information and use them to make superior judgments of the public information. Although the implications for information asymmetry might be different, the intensity of informed trading increases around a news release in both models. On the other hand, if informed traders deem a news release to be a substitute for private information, then they are less likely to gather private information before the release of public information and trade on it (Grundy and McNichols, 1989). Thus, a news release could either increase or decrease the intensity of informed trading and the degree of information asymmetry.⁵

News releases could also affect the incentive of uninformed traders to trade. Uninformed traders are more likely to be small and/or individual investors that are resource-constrained and less likely to gather costly private information. Hence, they are likely to rely on news releases to make their trading decisions. For example, Lee (1992) and Barber and Odean (2008) find empirical evidence that individual investors' trades are likely to cluster in firms with more frequent news release. However, it is ambiguous how uninformed investors would trade strategically in the presence of news releases. For example, if uninformed traders believe that informed traders are more likely to trade around news releases, uninformed investors would have incentives to stay away from trading to avoid being taken advantage by better informed traders, reducing trades around

⁵ See Livne (2000) for a model that incorporates both characteristics of news releases.

news releases. On the other hand, Admati and Pfleiderer (1988) show that, if uninformed investors have the discretion to time trades, they have incentives to cluster trades when market is thick enough to reduce adverse selection costs. Therefore, whether uninformed investors increase trades or avoid trading around public news releases is an empirical question. Also, individual investors might engage in trades that provide liquidity to institutional investors, resulting increased uninformed trades around news events (see Kaniel, Saar, and Titman, 2008; Kaniel, Liu, Saar, and Titman, 2012).

To examine how informed and uninformed trades respond to news releases, we decompose the *PIN* into trading intensities of informed and uninformed traders, similarly to Brown and Hillegeist (2007) who decompose the *PIN* and examine each component separately.⁶ By decomposing the *PIN*, we examine the impacts of news release on the trading intensities of informed and uninformed traders separately, which is one of the key features of this paper. We find a significantly higher trading intensity of uninformed traders in firms with more frequent stream of news release. Though the trading intensity of informed traders is also higher in firms with more frequent news release, it is outweighed by the increase in uninformed trading, resulting in a lower *PIN* for these firms. As is suggested by existing market microstructure theories (Glosten and Milgrom, 1985; Kyle, 1985; Easley et al., 1996), the presence of uninformed traders mitigates the information asymmetry in the market. Hence, for firms with more frequent news release, the significant increase in trading by uninformed traders relative to informed traders explains the lower information asymmetry for these firms.

⁶ A recent paper by Wei, Gerace and Frino (2012) studies the time series properties of informed and uninformed trading intensities estimated from *PIN* and their relation to size, value and liquidity.

Our study contributes to the understanding of the effects of news releases on investors' trading behavior and price formation,⁷ particularly in relation to the role of uninformed traders. We show that the reduced information asymmetry in firms with more frequent news release is driven by the increased trading by uninformed investors who might base their trading decisions primarily on public news. Therefore, the trades of uninformed investors are crucial in bringing about the economic benefits of lowering information asymmetry due to increased disclosure. This finding also supports market regulators' objective to increase the frequency of news disclosure and to level the playing field for all investors. Finally, prior literature has shown that information asymmetry affects the cost of capital and expected return of stocks.⁸ Our finding highlights the potential role of news release in reducing the cost of capital since greater frequency of news release is likely to decrease the information asymmetry.

The rest of the paper is organized as follows: Section 2 introduces the construction of key variables and the empirical methodology; Section 3 describes the sample and data; Section 4 presents the results of empirical analyses; and finally Section 5 concludes the paper.

⁷ There is also a growing literature studying the trading and price patterns in response to public information arrival as measured by media news or firm announcements. For example, Kalev, Liu, Pham and Jarnecic (2004) study the intraday return volatility around firm-specific announcements; Tetlock (2010) and Riordan, Storkenmaier, Wagener and Zhang (2012) examine the information asymmetry metrics around media news days.

⁸ Previous literature has shown that information asymmetry impedes investment and increases the cost of capital (e.g., Diamond and Verrecchia, 1991; Easley and O'Hara, 2004). See Verrecchia, 2001 for a survey. Easley, Hvidkjaer and O'Hara (2002, 2010) show that information asymmetry is a factor that impacts the cross section of expected return. .

2. Variable Construction and Methodology

2.1 Measuring the frequency of news release

Our source of news release is all news items appearing on the website www.MarketWatch.com for each firm. The website is a financial information services provider wholly owned by Dow Jones & Company, Inc. There are two merits in using news released on www.MarketWatch.com as a proxy of firm-specific public information. First, www.MarketWatch.com provides a broad coverage of relevant firm-specific public news, including company press release via Business Wire, PR Newswire, Market Wire, and Prime Zone, SEC filings by Edgar Online, and other sources such as Reuters, New York Times, CBS News, FT.com, TheStreet.com, The Wall Street Journal Online, among others. Second, the news on this website is displayed in a manner that allows us to easily search and download the date, time, and headline for each news item using an automated computer algorithm, thus making it convenient to collect a large amounts of data.⁹

We measure the frequency of news for each firm as the number of days with news (*NEWSDAYS*) appearing on www.MarketWatch.com during the sample period. An alternative measure of the frequency of news could be the number of news items (*YEARNEWS*) appearing on www.MarketWatch.com during the sample period. Compared with the number of news items, the number of news days has the following advantages as the measure of news frequency. First, the use of number of news days mitigates the problem of double counting the same news story reported by different news sources which appears as multiple news items on the website. Thus, a higher number of news items during a specific day may not necessarily implies greater flow of information.

⁹ Zdorovtsov (2009) also uses the news extracted from this source to study the effect of information flow on trading activities and stock return volatility.

Second, the distribution of the number of news items is highly skewed and is dominated by a few firms which have a large number of news items almost every day. In 2004, the median (mean) number of news items per firm is 86 (116) for all firms in our sample, while the median (mean) value of the number of days with news is 49 (58). The skewness of the distribution of the number of news items is much higher than that of the number of news days.¹⁰ Although there might be a loss of information from assigning the value of 1 irrespective of the number of news item during a specific day, the use of number of news days has the benefit of mitigating any potential distortion in the data as mentioned above. Therefore, our discussion is based on the results using the number of news days as the proxy of news frequency. Measuring the frequency of news using the number of news items gives quantitatively similar results which are not reported but available from the authors upon request.

2.2 Measuring information asymmetry

Our primary measure of information asymmetry is the probability of information-based trading (*PIN*) which is calculated as the relative intensity of informed trading to the total trading. The intensities of informed trading and uninformed trading are estimated from the sequential trade model described by Easley et al. (1996). In this model, both informed trades and uninformed trades are assumed to arrive in the market following an independent Poisson process. Informed trades arrive at the rate of *MU* only on the days when a private news event occurs with a probability of *ALPHA*. Informed traders buy when the news is positive and sell when the news is negative. The arrival rates of

¹⁰ We use a logarithmic transformation of the frequency of news release to mitigate the effect of the skewed distribution of news across firms. Our results also hold if we mitigate the effect of outliers by excluding firms falling in the top and bottom 1% of the distribution of the measure of news frequency.

uninformed buy and sell trades are both *EPSILON* and are independent of the occurrence and sign of the private news event. Thus the average number of informed trades is the product of *ALPHA* and *MU*, and that of uninformed trades is ($2 * EPSILON$). We use ($ALPHA * MU$) as the proxy of the intensity of informed trading (*INFORM*) and ($2 * EPSILON$) as the proxy of the intensity of uninformed trading (*UNIFORM*). The relative intensity of informed trading to uninformed trading is the probability of information-based trading (*PIN*) which is calculated as the ratio of the informed trading intensity to the total trading intensity,

$$PIN = \frac{ALPHA * MU}{ALPHA * MU + 2 * EPSILON} = \frac{INFORM}{INFORM + UNIFORM} \quad (1)$$

We estimate the individual components in Eq. (1) by numerically maximizing the likelihood function as specified in Easley et al. (1996).¹¹ However, Yan and Zhang (2012) find that boundary solutions in numerical maximization methods can cause a bias in the estimate of *PIN*. Thus, we adopt the algorithm in Yan and Zhang (2012) to select various sets of initial values for optimization, and choose the set of parameter estimates producing the highest value of the likelihood function.¹²

¹¹ See Easley et al. (1996) for the details of the model and the estimation of the model parameters.

¹² Lin and Ke (2011) document a downward bias in estimating *PIN* caused by the floating-point exception (FPE). We assume an equal arrival rate for the uninformed buy and sell trades, which significantly reduces but does not totally remove the occurrence of FPE.

2.3 Modeling the relationship between the frequency of news release and information asymmetry

2.3.1 Single equation estimation

The primary objective of our paper is to study the relation between firm specific news release and information asymmetry. We start with a single equation OLS model that examines this relationship. To model the information asymmetry, we follow the empirical specification in Brennan and Subrahmanyam (1995) and Roulstone (2003):

$$\begin{aligned} \ln(PIN_i) = & \alpha_0 + \alpha_1 \ln(NEWSDAYS_i) + \alpha_2 \ln(VOL_i) + \alpha_3 \ln(SIZE_i) \\ & + \alpha_4 \ln(NANLY_i) + \alpha_5 \ln(PRICE_i) + \alpha_6 \ln(RETVOL_i) + \varepsilon_i \end{aligned} \quad (2)$$

where we include *NEWSDAYS* in addition to the variables used in prior studies. Other variables include trading volume (*VOL*) measured as the average daily number of trades during the year,¹³ firm size (*SIZE*) measured as the average daily market capitalization during the year, the number of analysts following (*NANLY*) measured as the number of analysts releasing yearly earnings forecasts for a firm during the year, the price level (*PRICE*) measured as the average daily closing stock price during the year, and return volatility (*RETVOL*) measured as the standard deviation of daily stock returns during the year. As large trading volume enables market makers to reduce inventory risk (Stoll, 1978; Ho and Stoll, 1980), recover losses from trading with informed traders and reduce the bid-ask spread (McInish and Wood, 1992), we expect *VOL* to have a negative impact on the *PIN*. As larger firms have better information environment, thus lower information

¹³ We measure volume as the number of trades following the finding by Jones, Kaul and Lipson (1994) that number of transactions is more relevant for studying the impact of trading on stock price. Alternative measures of trading volume, such as share turnover (the fraction of shares outstanding traded), yield similar results.

asymmetry, we expect firm size (*SIZE*) to have a negative impact on the *PIN*. Brennan and Subrahmanyam (1995) and Roulstone (2003) find that the number of analysts following (*NANLY*) is negatively related with the measures of illiquidity and information asymmetry since analysts supply information to the market. Due to discreteness in prices, stocks with a low price (*PRICE*) usually tend to have high spreads and high price impact of trades (Jegadeesh and Subrahmanyam, 1993). Finally, prior research has documented a negative relationship between return volatility and liquidity as market makers face higher inventory risk and adverse selection risk when the stock returns are more volatile (Stoll, 1978; Jegadeesh and Subrahmanyam, 1993). Thus, we expect a positive coefficient on *RETVOL*.

2.3.2 System of equations

It is possible that firms with higher information asymmetry choose to release greater amount of news to reduce the high information asymmetry. Coller and Yohn (1997) suggest that firms issue management forecasts to reduce information asymmetry prior to an earnings announcement. Leuz and Verrecchia (2000) indicate that firms may strategically pick the level of disclosure by choosing between different financial reporting regimes. Thus the firms' disclosure policy may be affected by the information asymmetry in the market. In addition, news media are also likely to gather information about firms with high information asymmetry since it is likely that there is a greater demand for information about such firms. Hence, news release and information asymmetry are likely to be endogenously determined and need to be modeled simultaneously. We use a

simultaneous equation system that models both the information asymmetry and the frequency of news release.

The model for information asymmetry remains the same as described above in equation (2). To model the frequency of news release, we draw from prior literature on the determinants of firms' disclosure policy (Lang and Lundholm, 1993; Brown and Hillegeist, 2007). Specifically, in addition to the proxy for information asymmetry, we include several variables as control variables. Firm size (*SIZE*) is an important determinant for the press to follow a firm. Larger firms might have more news to be released, thus being covered more often by the press. The number of analysts following (*NANLY*) is also another important determinant of news coverage. Analysts generate information about firms through their recommendations and reports and these are likely to be picked up by the press. Also, as the press is likely to follow firms in which there is greater interest from institutional investors, we expect the number of institutional investors holding a firm's stocks (*NINST*) is positively related to the number of news days. Firms with greater analysts' forecast error in the quarterly earnings announcements (*FERR*) are also more likely to be covered in the news. We measure *FERR* in three steps. In the first step we measure how far away the analyst forecast is from the actual earnings by calculating the absolute value of the difference between the consensus quarterly earnings forecast in the first month of every quarter and the reported quarterly earnings. Second, we scale the above absolute difference by the average daily price during the first month of every quarter to reduce heteroskedasticity. Finally, we average the values from the second step over the 5-year period before the sample year to obtain *FERR*. When a firm raises large amount of capital, it is also likely to be covered by the press due to

investor demand for information of the firm. We include a dummy variable indicating new financing activity (*NEWFIN*) which takes the value of one if a firm has any equity issuance above \$10 million or any debt issuance above \$1 million in the current and the following fiscal years, and takes the value of zero otherwise. Lastly, we include industry dummy variables (*IND*).¹⁴ All the variables, which are logarithm transformed except for the dummy variables, are expected to capture the cross-sectional variation in the demand for news by market participants. Thus, the model for the frequency of news release is specified as follows,

$$\begin{aligned} \ln(NEWSDAYS_i) = & \beta_0 + \beta_1 \ln(PIN_i) + \beta_2 \ln(SIZE_i) + \beta_3 \ln(NANLY_i) \\ & + \beta_4 \ln(NINST_i) + \beta_5 \ln(FERR_i) + \beta_6 NEWFIN_i + \sum_{k=1}^9 \gamma_k IND_{k,i} + \eta_i \end{aligned} \quad (3)$$

We estimate the relationship between the information asymmetry (*PIN*) in Eq. (2) and the frequency of news release (*NEWSDAYS*) in Eq. (3) using two-stage least square (2SLS) regression. Specifically, the variables *NINST*, *FERR*, *NEWFIN* and *INDs* are unique instrumental variables for *NEWSDAYS*, and *PRICE* and *RETVOL* are those for the information asymmetry variable following Brennan and Subrahmanyam (1995).

3. Sample and Data

3.1 Sample

Our sample comprises 1031 firms with stocks traded on NYSE during the calendar year 2004. We start the sample selection process by including all common

¹⁴ Firms are classified into 10 industries and the industry classification scheme is obtained from the website of Kenneth French.

stocks which were traded on the NYSE during the year and included in the CRSP database. We include only NYSE stocks in our analysis to abstract away from differences in market making mechanisms between different exchanges. Stocks other than common stocks, i.e., those with share code other than 10 and 11, are excluded, since their trading characteristics might differ from those of ordinary equities. Consistent with extant literature, we only include stocks whose average monthly closing price in the year is greater than \$5 to avoid the influence of dollar and penny stocks. After applying the above filters, 184 stocks out of the original 1535 stocks are dropped from the sample. In estimating *PIN* we lose a further 243 stocks which have extremely large daily number of trades that causes data overflow during the MLE estimation. We also require the stocks to have news appearing on www.MarketWatch.com during 2004, which restricts the final sample to 1031 stocks.

We obtain the data from the following sources: news data from www.MarketWatch.com, daily stock price and trading data from CRSP, intraday transaction data from NYSE TAQ to estimate the *PIN* and other information asymmetry proxies, quarterly earnings and capital financing data from COMPUSTAT, analysts' earnings forecasts and other related data from I/B/E/S, and institutional holding data from Thomson Financial (13F filing).

3.2 Descriptive statistics

The descriptive statistics of the firms in the sample are reported in Table 1. In our sample, the average firm is reported in the news for about 58 days during the year 2004, and has 116 articles written about it in 2004. The relatively frequent news release for the

firms in our sample is most likely due to the fact that these are relatively large firms listed on the NYSE that attract extensive attention from investors. The average market capitalization (*SIZE*) of firms in our sample is \$ 2.6 billion. The firms in our sample are also actively traded. An average firm in the sample has about 782 trades in a day. There are about 55 informed trades and 714 uninformed trades in a day for an average firm in the sample.¹⁵ The average probability of information-based trading (*PIN*) for the firms in the sample is about 10%.¹⁶ The average firm in our sample has about 7 analysts that release annual earnings forecast, indicating that analysts actively follow the sample firms. Further, average daily return volatility (*RETVOL*) is 1.83% and the average price is about \$32. The average forecast error in the consensus analyst earnings forecast (*FERR*) is about 55 basis points of the stock price. Finally, about 83% of firms in the sample have new financing activity during either the sample year or the following year.

Table 2 reports the correlation coefficients between different firm characteristics. Both Pearson and Spearman (in *italic*) correlation coefficients are reported in this table. For most variable pairs, the two correlation coefficients do not differ significantly, which indicates that non-linearity in the relationship between the variables might not be a significant concern. We find high correlation between the number of days with news (*NEWSDAYS*) and the number of news items during the year (*YEARNEWS*). The Pearson correlation coefficient between the two variables is 0.747 and the Spearman rank correlation coefficient is 0.946, which indicates that the measurements from these two

¹⁵ The sum of average informed trades and uninformed trades is close to but does not exactly equal to the average number of trades, which is due to the noise in the estimation of the PIN model.

¹⁶ The mean value of PIN seems to be lower than that reported in Easley, Hvidkjaer and O'Hara (2002). We estimated PINs for NYSE common stocks for the period from 1993 to 2001 using our algorithm and compared our results with those by Easley et al (2002) from the website of Hvidkjaer. The two sets of PIN calculations are of similar magnitude and have very high correlation (over 0.9). The average PIN in our sample year (2004) is likely to be lower because PIN decreases over time, especially after the decimalization in year 2001.

proxies yield similar metrics for the frequency of news release. However, for reasons explained in Section 2.1, we conduct our analysis and report results using *NEWSDAYS*. Importantly, the correlation coefficient between the frequency of news release, *NEWSDAYS*, and the proxy for the information asymmetry (*PIN*) is significantly negative, which suggests that frequent news releases mitigate asymmetric information. Finally, firms with more frequent news release tend to have more trading, larger size, more analysts following, higher price and lower return volatility, all of which conform with findings in prior literature.

4. Empirical Results

4.1 Relationship between the frequency of news release and information asymmetry

4.1.1 Single equation regression results

In this section we first present results from estimating equation (2) using OLS in a single equation setting. Table 3 shows the results of this estimation. We present three sets of results, because *VOL* and *SIZE* are highly correlated (Spearman correlation coefficient = 0.802). In each of the two specifications where either *VOL* or *SIZE* is included separately, the coefficient on *NEWSDAYS* is significantly negative, suggesting that firms with greater number of news items are associated with lower information asymmetry. In Model 3 where both *VOL* and *SIZE* are included simultaneously in the model, the coefficient on *NEWSDAYS* is still statistically significant, although its magnitude is slightly smaller (-0.107). As both *PIN* and *NEWSDAYS* are logarithm transformed variables, the coefficient can be interpreted as an elasticity measure, which indicates that one percent increase in *NEWSDAYS* is associated with a decrease of around 10.7 basis

points in the *PIN*. This relationship offers support for the argument by market regulators that greater disclosure and public information helps alleviate information asymmetry.

We also find in Table 3 that the relation between most of the control variables and *PIN* is consistent with findings documented in prior literature. Trading volume is strongly negatively related with information asymmetry (*PIN*), which is consistent with the findings in the prior studies (Stoll, 1978; Ho and Stoll, 1980; McNish and Wood, 1992). Similar to the findings by Brennan and Subrahmanyam (1995) and Roulstone (2003), we also find that higher number of analysts following a stock is associated with lower information asymmetry. Further, stocks with higher stock price tend to have lower information asymmetry (Stoll (1978), Jegadeesh and Subrahmanyam (1993) and Brennan and Subrahmanyam (1995)). However, the coefficient on *RETVOL* is negative, which is opposite to the expected sign. Finally, we find that firm size is significantly negatively related with information asymmetry, which is consistent with our expectation.

4.1.2 System of equations regression results

In this section we present the results from estimating the simultaneous system of equations (Eq. (2) and (3)) that examines the cross-sectional relationship between the frequency of news release and information asymmetry in a multivariate setting. Table 4 presents the two-stage least square (2SLS) regression results. In the second stage equation for the *PIN*, we find that the coefficient on *NEWSDAYS* is significantly negatively (the coefficient = -0.216 and t-statistic = -3.18), suggesting that firms with more frequent news release have lower information asymmetry even after controlling for the endogenous relation between the two variables.

Turning to the second stage *NEWSDAYS* equation, we find that after controlling for the endogeneity between *PIN* and *NEWSDAYS*, *NEWSDAYS* is significantly and negatively related to *PIN*, which highlights the necessity of addressing the endogenous relationship between frequency of news release and information asymmetry. Further, we find that firms with higher analysts' forecast error and new financing activity tend to have more frequent news release as the coefficients on *FERR* and *NEWFIN* are both significantly positive. Our result supports the conjectures made by Brown and Hillegeist (2007) that these variables capture the variation in the demand for news, justifying the use of these variables as instruments for the frequency of news release. We also find that firms that are larger and more actively followed by analysts have more frequent news release. However, we find that greater number of institutional holders does not necessarily increase public information disclosure since we find that the coefficient on *NINST* is not significantly different from zero.

In sum, the results documented in Tables 3 and 4 suggest that firms with greater frequency of news release are associated with lower information asymmetry. Our next step is to examine how this relationship is manifested. The traditional theories of market microstructure suggest that greater intensity of informed (uninformed) trading is associated with higher (lower) level of information asymmetry (Kyle, 1985; Easley et al, 1996). We conjecture that different trading intensities of informed and uninformed investors in response to news affect the overall information asymmetry in the market. To examine this conjecture, we investigate the relationship between frequency of news release and trading intensities of informed and uninformed traders separately.

4.2 Relationship between the frequency of news release and the intensities of informed trading and uninformed trading

To study the relation between the frequency of news release and the intensities of informed trading and uninformed trading, we first sort firms into three equal-size groups based on the frequency of news release and then compare the means and medians of the intensities of informed trading (*INFORM*) and uninformed trading (*UNIFORM*) across the three news groups. As defined in the Section 2, *INFORM* is the product of the probability of a private news event (*ALPHA*) and the arrival rate of informed trades (*MU*), and *UNIFORM* is the arrival rate of uninformed trades ($2*EPSILON$). The underlying parameters, *ALPHA*, *MU* and *EPSILON*, are estimated from the sequential trade model described in Easley et al (1996).

We further refine the above sorting process and incorporate firm size into the analysis. We first sort firms into three groups based on *SIZE*, and within each *SIZE* group we further sort firms into three groups based on *NEWSDAYS*. Then we compare the difference in the means and medians of *INFORM* and *UNIFORM* across the *NEWSDAYS* groups within each *SIZE* group.

The results are reported in Table 5 where Panel A shows the results for the full sample and Panels B to D show results for small, medium and large firms respectively. In each panel, columns 2 to 4 report the mean and median (shown in *italics*) values of the trading intensities for firms with low, medium and high frequency of news release. Column 5 reports the t-statistic for the test of equality of the mean values of informed and uninformed trading intensities between high and low *NEWSDAYS* firms. And the last column reports the z-statistic from the Wilcoxon rank-sum test.

As seen from the table, both the mean and median values (in italics) of *INFORM* and *UNIFORM* increase with *NEWSDAYS*. For the full sample, the mean value of *INFORM* almost doubles from 0.391 for low *NEWSDAYS* firms to 0.73 for high *NEWSDAYS* firms and that of *UNIFORM* more than triples from 3.409 for low *NEWSDAYS* firms to 11.699 for high *NEWSDAYS* firms. A similar pattern exists in the median values. Both the t-test and the Wilcoxon rank-sum test reject the equality of values of both *INFORM* and *UNIFORM* between high and low *NEWSDAYS*. Although our result suggests that firms with more frequent news release are associated with more intense trading by both types of traders, the increase in trading is significantly higher for uninformed traders than for informed traders. As a result, the relative trading intensity of informed to uninformed, which is the probability of information-based trading (*PIN*), decreases with *NEWSDAYS*. Turning to Panels B to D, we find that the intensities of both informed and uninformed trading are also higher in high *NEWSDAYS* firms compared with low *NEWSDAYS* firms in each of the three sub samples based on size. Further, we also find that the intensity of uninformed trading increases much more significantly with *NEWSDAYS* than the intensity of informed trading in every size sub samples. Therefore, our results are not driven by the firms in particular size groups.

We reconcile our results with those in previous literature that imply strong reaction of uninformed trades to public information. First, our result is consistent with uninformed investors relying on public news when making their trading decisions (Lee, 1992; Barber and Odean, 2008). Our result also suggests that uninformed traders might choose to cluster in firms with more frequent news release since a ‘thick’ market can reduce the probability of trading against informed traders (Admati and Pfleiderer, 1988).

Our findings also do not rule out the possibility that uninformed traders are providing liquidity to informed traders around the release of news (Kaniel, Saar, Titman, 2008; Kaniel, Liu, Saar, Titman, 2008). As the increase in liquidity also decreases the *PIN* (Easley et al., 1996), our results are also consistent with this conjecture. Prior market microstructure literature has conjectured that a greater level of uninformed trading relative to informed trading leads to lower information asymmetry (Kyle, 1985; Easley et al., 1996). Our empirical finding confirms this conjecture by showing that information asymmetry is mitigated due to higher intensity of uninformed relative to informed trading in response to the release of public information. Therefore, our findings highlight the important role of news release that facilitates the trading by uninformed traders and plays an important role in reducing information asymmetry in the market.

4.3 Robustness tests: relationship between the frequency of news release and alternative proxies for information asymmetry

In this section, we present the results of additional tests that examine the relationship between the frequency of news release and alternative proxies for information asymmetry. Specifically, we replicate the single equation analysis in Section 4.1 using two alternative proxies for information asymmetries – permanent price impact of trades (*PPI*) and the adverse selection component of bid-ask spread (*ASC*).

Following Hasbrouck (1991), we estimate the permanent price impact of trades (*PPI*) from the impulse-response coefficients between price changes and trading using the following VAR model of quote revision (R_t) and trading-related variables (X_t),

$$R_t = \sum_{i=1}^5 a_i R_{t-i} + \sum_{j=0}^5 b_j X_{t-j} + V_{1,t} \quad (4)$$

$$X_t = \sum_{k=1}^5 c_k R_{t-k} + \sum_{l=1}^5 d_l X_{t-l} + V_{2,t}. \quad (5)$$

X_t is a vector of trading-related variables which includes a dummy variable indicating sign of the trade, the product of sign of the trade and number of shares traded, and the product of sign of the trade and square root of number of shares traded to capture the decreasing marginal price impact.¹⁷ For each trade, we calculate the change in the midpoint of quotes, R_t , as the difference between the midpoint of first updated quotes within 5 seconds after the trade and the midpoint of the quotes prevailing when the trade occurred. Based on the estimated coefficients of the VAR model in equations (4) and (5), we calculate the impulse-response coefficients between trading variables and price revisions. The permanent price impact of trades is estimated as the cumulative price response to a trading of 1000 shares.¹⁸ We scale the cumulative response by the average stock price to make it scale-free and comparable across stocks.¹⁹

We use the adverse selection component of traded spread (*ASC*) as another proxy for information asymmetry, which is estimated from the three-way spread decomposition method in Huang and Stoll (1997). They construct a model in which the trade-to-trade

¹⁷ We classify each trade into buyer-initiated or seller initiated according to the algorithm developed by Lee and Ready (1991).

¹⁸ We calculate the price responses to the given trading impulse after the trading up to 20 steps, and then sum up these price responses to obtain the cumulative price response. We stop at 20 steps because the response coefficients tend to decay quickly and are negligible beyond 20 steps.

¹⁹ Please refer to Hasbrouck (1991) for more detailed discussion on the construction and estimation of the model.

price change reflects the information revealed in trading, the compensation for inventory cost and order processing cost of market making,

$$\Delta P_t = \frac{S}{2} Q_t + (\alpha + \beta - 1) \frac{S}{2} Q_{t-1} - \alpha \frac{S}{2} (1 - 2\pi) Q_{t-2} + e_t, \quad (6)$$

where ΔP_t is the change in transaction price from the previous trade, Q_t , Q_{t-1} and Q_{t-2} are buy-sell trade indicators for the current trade and the last two trades respectively, and e_t is serially uncorrelated public information shock. Estimating Eq. (6) and the autocorrelation coefficient of the trade indicator simultaneously yields the estimates of model parameters. The set of parameters include the traded spread S and the autocorrelation coefficient of trade indicator $(1 - 2\pi)$. Also included are the adverse selection component α and the inventory cost component β , where $(1 - \alpha - \beta)$ is the order processing cost component of the traded spread.²⁰ We are interested in α , the adverse selection component of the traded spread (ASC), which is driven by information asymmetry.

Table 6 shows the results of estimating Eq. (2) using either the permanent price impact of trades (PPI) or the adverse selection component of bid-ask spread (ASC).²¹ For simplicity, we only report the coefficient on *NEWSDAYS*, the variable of interest. We find that the coefficient on *NEWSDAYS* remains statistically negative in both regressions. Thus, the regression results using alternative proxies for information asymmetry confirm our finding that firms with greater frequency of news release have lower information asymmetry.

²⁰ See Huang and Stoll (1997) for more details. on the construction and estimation of the model.

²¹ We use $\ln(1+ASC)$ as the dependent variable to maintain its economic interpretation as the percentage of bid-ask spread. Adding 1 also helps to solve the issue of negative value of estimated ASC , which is caused by the positive serial correlation in order flows.

5. Conclusion

Prior empirical research based on event studies showed that information asymmetry increases around event dates such as earnings and dividend announcements. However, these empirical results could be driven by informed traders who might react more quickly to information than uninformed traders. In contrast, our study examines the responses of both informed and uninformed trades to news releases over a longer time horizon. We find that firms with more frequent news releases are associated with lower information asymmetry. We use three measures of information asymmetry: *PIN*, the permanent price impact and the adverse selection component of bid-ask spread.

In particular, by decomposing the *PIN* into trading intensities of informed and uninformed traders, we examine why firms with more frequent news releases have lower information asymmetry. As the frequency of news release increases, we find that the intensity of uninformed trading increases much more than that of informed trading, thus lowering the *PIN* for firms with more frequent news release. Our result holds even after controlling for firm size. Thus, our findings not only emphasize the importance of news release in leveling the playing field for investors but also highlight the important role of uninformed investors in reducing the cost of information asymmetry. Our findings also support the objective of market regulators that emphasize the role of public disclosure of information.

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Table 1**Descriptive statistics**

This table presents the descriptive statistics for a sample of 1031 firms with stocks traded on NYSE during the sample year 2004. *NEWSDAYS* is the number of days with news appearing on www.MarketWatch.com for a firm during the sample year. *YEARNEWS* is the total number of news items appearing on www.MarketWatch.com for a firm during the sample year. *INFORM* is the intensity of informed trading, *UNIFORM* is the intensity of uninformed trading, and *PIN* is the probability of information-based trading defined as the ratio of the informed trading intensity to the total trading intensity, all of which are estimated from a sequential trade model described in Easley et al (1996) using intraday data in year 2004. *VOL* is the average of daily number of trades during the sample year. *SIZE* is firm size measured as the average of daily market capitalization during the sample year. *NANLY* is the number of analysts following a firm measured as the number of analysts making yearly earnings forecasts for a firm during the sample year. *PRICE* is the average daily closing stock price during the sample year. *RETVOL* is return volatility measured as the standard deviation of daily stock returns during the sample year. *NINST* is the number of institutional investors holding a firm's stocks at the end of previous year. *FERR* is the analysts' forecast error measured as the average value of the price-scaled deviation of the consensus quarterly earnings forecast in the first month of every quarter from the reported quarterly earnings over the 5-year period before the sample year. *NEWFIN* is a dummy variable which equals to one if a firm has any equity issuance above \$10 million or any debt issuance above \$1 million in the fiscal years 2004 and 2005 and zero otherwise.

Variable	Mean	Std.	1 st Quartile	Median	3 rd Quartile
<i>NEWSDAYS</i>	57.539	32.182	38	49	66
<i>YEARNEWS</i>	115.825	141.409	63	86	129
<i>PIN</i>	0.102	0.056	0.062	0.085	0.126
<i>INFORM</i> (100s)	0.553	0.260	0.378	0.548	0.706
<i>UNIFORM</i> (100s)	7.142	5.533	2.883	5.984	10.019
<i>VOL</i> (100s)	7.815	5.980	3.307	6.585	10.858
<i>SIZE</i> (\$B)	2.587	4.393	0.519	1.153	2.606
<i>NANLY</i>	7.266	5.558	3	6	11
<i>PRICE</i>	31.790	34.374	17.713	27.422	39.815
<i>RETVOL</i> (%)	1.831	0.696	1.324	1.738	2.202
<i>NINST</i> (100s)	1.576	1.060	0.890	1.330	1.980
<i>FERR</i> (%)	0.547	0.768	0.151	0.296	0.555
<i>NEWFIN</i>	0.829	0.376	1	1	1

Table 2**Correlation matrix of variables**

This table reports the correlation coefficients between variables for a sample of 1031 firms with stocks traded on NYSE during the sample year 2004. *NEWSDAYS* is the number of days with news appearing on www.MarketWatch.com for a firm during the sample year. *YEARNEWS* is the total number of news items appearing on www.MarketWatch.com for a firm during the sample year. *INFORM* is the intensity of informed trading, *UNIFORM* is the intensity of uninformed trading, and *PIN* is the probability of information-based trading defined as the ratio of the informed trading intensity to the total trading intensity, all of which are estimated from a sequential trade model described in Easley et al (1996) using intraday data in year 2004. *VOL* is the average of daily number of trades during the sample year. *SIZE* is firm size measured as the average of daily market capitalization during the sample year. *NANLY* is the number of analysts following a firm measured as the number of analysts making yearly earnings forecasts for a firm during the sample year. *PRICE* is the average daily closing stock price during the sample year. *RETVOL* is return volatility measured as the standard deviation of daily stock returns during the sample year. Pearson correlation coefficients are reported in the upper-right block and Spearman ones are reported in the lower-left block in *Italic*. The p-values of all correlation coefficients are less than 5% except for those indicated with asterisk.

	<i>NEWSDAYS</i>	<i>YEARNEWS</i>	<i>PIN</i>	<i>INFORM</i>	<i>UNIFORM</i>	<i>VOL</i>	<i>SIZE</i>	<i>NANLY</i>	<i>PRICE</i>	<i>RETVOL</i>
<i>NEWSDAYS</i>		0.747	-0.492	0.564	0.662	0.664	0.561	0.535	0.170	-0.140
<i>YEARNEWS</i>	<i>0.946</i>		-0.296	0.342	0.422	0.430	0.372	0.326	0.155	-0.087
<i>PIN</i>	<i>-0.654</i>	<i>-0.669</i>		-0.662	-0.726	-0.719	-0.379	-0.584	-0.139	0.053*
<i>INFORM</i>	<i>0.571</i>	<i>0.564</i>	<i>-0.621</i>		0.864	0.870	0.617	0.656	0.057*	-0.259
<i>UNIFORM</i>	<i>0.683</i>	<i>0.688</i>	<i>-0.908</i>	<i>0.880</i>		0.997	0.720	0.741	0.120	-0.217
<i>VOL</i>	<i>0.681</i>	<i>0.686</i>	<i>-0.901</i>	<i>0.887</i>	<i>1.000</i>		0.742	0.742	0.118	-0.220
<i>SIZE</i>	<i>0.548</i>	<i>0.551</i>	<i>-0.709</i>	<i>0.735</i>	<i>0.802</i>	<i>0.802</i>		0.549	0.203	-0.385
<i>NANLY</i>	<i>0.562</i>	<i>0.549</i>	<i>-0.675</i>	<i>0.670</i>	<i>0.751</i>	<i>0.751</i>	<i>0.697</i>		0.130	-0.262
<i>PRICE</i>	<i>0.167</i>	<i>0.171</i>	<i>-0.347</i>	<i>0.248</i>	<i>0.330</i>	<i>0.327</i>	<i>0.552</i>	<i>0.327</i>		-0.264
<i>RETVOL</i>	<i>-0.115</i>	<i>-0.120</i>	<i>0.096</i>	<i>-0.275</i>	<i>-0.207</i>	<i>-0.209</i>	<i>-0.580</i>	<i>-0.277</i>	<i>-0.525</i>	

* P-value > 5%

Table 3**Relation between the frequency of news releases and PIN**

This table reports the OLS regression results of the following equation for a sample of 1031 firms with stocks traded on NYSE during the sample year 2004,

$$\begin{aligned} \ln(PIN_i) = & \alpha_0 + \alpha_1 \ln(NEWSDAYS_i) + \alpha_2 \ln(VOL_i) + \alpha_3 \ln(SIZE_i) \\ & + \alpha_4 \ln(NANLY_i) + \alpha_5 \ln(PRICE_i) + \alpha_6 \ln(RETVOL_i) + \varepsilon_i \end{aligned}$$

PIN is the probability of information-based trading which is estimated from a sequential trade model described in Easley et al (1996). *NEWSDAYS* is the number of days with news appearing on www.MarketWatch.com for a firm during the sample year. *VOL* is the average of daily number of trades during the sample year. *SIZE* is firm size measured as the average of daily market capitalization during the sample year. *NANLY* is the number of analysts following a firm measured as the number of analysts making yearly earnings forecasts for a firm during the sample year. *PRICE* is the average daily closing stock price during the sample year. *RETVOL* is return volatility measured as the standard deviation of daily stock returns during the sample year. Regression coefficient and the corresponding t-statistics based on robust standard errors are reported.

Ind. Var.	Model 1		Model 2		Model 3	
	Coef.	T-Stat.	Coef.	T-Stat.	Coef.	T-Stat.
<i>INTERCEPT</i>	0.681	7.41	0.930	9.15	0.784	9.10
<i>Ln(NEWSDAYS)</i>	-0.122	-6.11	-0.180	-6.97	-0.107	-5.34
<i>Ln(VOL)</i>	-0.337	-23.78			-0.293	-16.20
<i>Ln(SIZE)</i>			-0.260	-18.86	-0.065	-4.59
<i>Ln(NANLY)</i>	-0.029	-2.26	-0.119	-6.95	-0.022	-1.76
<i>Ln(PRICE)</i>	-0.108	-7.79	-0.081	-3.68	-0.090	-6.30
<i>Ln(RETVOL)</i>	-0.167	-7.48	-0.570	-19.24	-0.253	-9.04
<i>Adj. R²</i>	0.817		0.732		0.821	

Table 4**Relation between the frequency of news releases and PIN: 2SLS regression results**

This table reports the 2SLS regression results of the following equation system for a sample of 1031 firms with stocks traded on NYSE during the sample year 2004,

$$\begin{aligned} \ln(PIN_i) &= \alpha_0 + \alpha_1 \ln(NEWSDAYS_i) + \alpha_2 \ln(VOL_i) + \alpha_3 \ln(SIZE_i) \\ &+ \alpha_4 \ln(NANLY_i) + \alpha_5 \ln(PRICE_i) + \alpha_6 \ln(RETVOL_i) + \varepsilon_i \\ \ln(NEWSDAYS_i) &= \beta_0 + \beta_1 \ln(PIN_i) + \beta_2 \ln(SIZE_i) + \beta_3 \ln(NANLY_i) \\ &+ \beta_4 \ln(NINST_i) + \beta_5 \ln(FERR_i) + \beta_6 NEWFIN_i + \sum_{k=1}^9 \gamma_k IND_{k,i} + \eta_i \end{aligned}$$

PIN is the probability of information-based trading which is estimated from a sequential trade model described in Easley et al (1996). *NEWSDAYS* is the frequency of news releases and measured as the number of days with news appearing on www.MarketWatch.com for a firm during the sample year. *VOL* is the average of daily number of trades during the sample year. *SIZE* is firm size measured as the average of daily market capitalization during the sample year. *NANLY* is the number of analysts following a firm measured as the number of analysts making yearly earnings forecasts for a firm during the sample year. *PRICE* is the average daily closing stock price during the sample year. *RETVOL* is return volatility measured as the standard deviation of daily stock returns during the sample year. *NINST* is the number of institutional investors holding a firm's stocks at the end of previous year. *FERR* is the analysts' forecast error measured as the average value of the price-scaled deviation of the consensus quarterly earnings forecast in the first month of every quarter from the reported quarterly earnings over the 5-year period before the sample year. *NEWFIN* is a dummy variable which equals to one if a firm has any equity issuance above \$10 million or any debt issuance above \$1 million in the fiscal years 2004 and 2005 and zero otherwise. *INDs* are industry dummies that are based on 10-industry classification scheme obtained from the website of Kenneth French. All variables in the regression are logarithm transformed except for dummy variables. Regression coefficient and the corresponding t-statistics based on robust standard error are reported. The coefficients of industry dummies in the 2nd equation are not reported.

Ind. Var.	Dep. Var. = $\ln(PIN)$		Dep. Var. = $\ln(NEWSDAYS)$	
	Coef.	T-Stat.	Coef.	T-Stat.
<i>INTERCEPT</i>	1.185	7.20	2.770	24.15
<i>Ln(NEWSDAYS)</i>	-0.216	-3.18		
<i>Ln(VOL)</i>	-0.306	-14.21		
<i>Ln(SIZE)</i>	-0.048	-3.24	0.124	4.74
<i>Ln(NANLY)</i>	-0.005	-0.32	0.72	6.42
<i>Ln(PRICE)</i>	-0.100	-6.06		
<i>Ln(RETVOL)</i>	-0.265	-9.63		
<i>Ln(PIN)</i>			-0.318	-4.19
<i>Ln(NINST)</i>			-0.075	-1.41
<i>Ln(FERR)</i>			0.091	5.59
<i>NEWFIN</i>			0.103	2.85
<i>INDs</i>	Not included		Included	
<i>Adj. R²</i>	0.817		0.471	

Table 5**Relation between the frequency of news releases and the intensities of informed trading and uninformed trading**

This table compares the difference in the intensities of informed trading and uninformed trading across firms with different levels of the frequency of news release (*NEWSDAYS*). *NEWSDAYS* is the number of days with news appearing on www.MarketWatch.com for a firm during the sample year. *INFORM* is the intensity of informed trading and *UNIFORM* is the intensity of uninformed trading, both of which are estimated from the sequential trade model described in Easley et al (1996) and expressed in 100 trades. *PIN* is the probability of information-based trading which is calculated as the ratio of the informed trading intensity to the total trading intensity, the sum of *INFORM* and *UNIFORM*. Firms are sorted into 3 equal-size groups based on *NEWSDAYS* either within the pooled sample or within 3 equal-size groups which are formed based on firm size. Then the mean and median (in *Italic*) values of each variable are reported for each group of firms. T is the t-statistic of the test of the null hypothesis that the mean values are the same for both high *NEWSDAYS* firms and low *NEWSDAYS* firms (High – Low = 0). Wilcoxon Z is the z-statistic of Wilcoxon rank-sum test (also called Mann-Whitney test) of the null hypothesis that the sample of high *NEWSDAYS* firms is drawn from the same population as the sample of low *NEWSDAYS* firms. All the test statistics are significant at less than 1% level.

Panel A: all firms

	<i>NEWSDAYS</i>			High - Low	
	Low	Medium	High	T-stat.	Wilcoxon Z
<i>INFORM</i>	0.391	0.545	0.730	19.65	16.04
	<i>0.385</i>	<i>0.531</i>	<i>0.712</i>		
<i>UNIFORM</i>	3.409	6.421	11.699	23.76	18.71
	<i>2.730</i>	<i>5.883</i>	<i>11.326</i>		
<i>PIN</i>	0.143	0.094	0.068	-20.85	-18.33
	<i>0.131</i>	<i>0.085</i>	<i>0.061</i>		

Panel B: small firms

	<i>NEUSDAYS</i>			High - Low	
	Low	Medium	High	T-stat.	Wilcoxon Z
<i>INFORM</i>	0.256	0.337	0.429	7.87	7.16
	<i>0.227</i>	<i>0.336</i>	<i>0.418</i>		
<i>UNIFORM</i>	1.688	2.450	4.037	8.79	8.10
	<i>1.143</i>	<i>2.152</i>	<i>3.629</i>		
<i>PIN</i>	0.178	0.153	0.114	-8.58	-7.57
	<i>0.166</i>	<i>0.145</i>	<i>0.102</i>		

Panel C: medium firms

	<i>NEUSDAYS</i>			High - Low	
	Low	Medium	High	T-stat.	Wilcoxon Z
<i>INFORM</i>	0.509	0.559	0.607	4.33	3.73
	<i>0.507</i>	<i>0.545</i>	<i>0.586</i>		
<i>UNIFORM</i>	4.652	6.406	8.096	8.67	7.73
	<i>4.195</i>	<i>5.944</i>	<i>7.466</i>		
<i>PIN</i>	0.115	0.089	0.076	-8.66	-8.10
	<i>0.116</i>	<i>0.084</i>	<i>0.071</i>		

Panel D: large firms

	<i>NEUSDAYS</i>			High - Low	
	Low	Medium	High	T-stat.	Wilcoxon Z
<i>INFORM</i>	0.647	0.770	0.867	7.87	7.20
	<i>0.645</i>	<i>0.776</i>	<i>0.888</i>		
<i>UNIFORM</i>	8.832	12.644	15.501	11.05	9.48
	<i>8.581</i>	<i>11.967</i>	<i>15.031</i>		
<i>PIN</i>	0.079	0.061	0.055	-7.41	-7.24
	<i>0.074</i>	<i>0.058</i>	<i>0.054</i>		

Table 6**Relation between the frequency of news releases and information asymmetry:
Robustness tests using alternative proxies of information asymmetry**

This table reports the OLS regression results of the following equation for a sample of 1031 firms with stocks traded on NYSE during the sample year 2004,

$$\begin{aligned} \ln(IA_i) = & \alpha_0 + \alpha_1 \ln(NEWSDAYS_i) + \alpha_2 \ln(VOL_i) + \alpha_3 \ln(SIZE_i) \\ & + \alpha_4 \ln(NANLY_i) + \alpha_5 \ln(PRICE_i) + \alpha_6 \ln(RETVOL_i) + \varepsilon_i \end{aligned}$$

The proxies of information asymmetry include: 1) *PPI*, the permanent price impact of a 1000-share trade which is estimated based on a VAR equation system of stock trades and quote revisions developed by Hasbrouck (1991); and 2) *ASC*, the adverse selection component of the traded spread which is estimated based on the spread decomposition procedure in Huang and Stoll (1997). *NEWSDAYS* is the number of days with news appearing on www.MarketWatch.com for a firm during the sample year. *VOL* is the average of daily number of trades during the sample year. *SIZE* is firm size measured as the average of daily market capitalization during the sample year. *NANLY* is the number of analysts following a firm measured as the number of analysts making yearly earnings forecasts for a firm during the sample year. *PRICE* is the average daily closing stock price during the sample year. *RETVOL* is return volatility measured as the standard deviation of daily stock returns during the sample year. Only the regression coefficient on $\ln(NEWSDAYS)$ and the corresponding t-statistics based on robust standard error are reported.

Panel A: Measuring information asymmetry as *PPI*

Ind. Var.	Dep. Var. = $\ln(PPI)$		
	Coef.	T-stat.	Adj. R^2
$\ln(NEWSDAYS)$	-0.052	-4.61	0.950

Panel B: Measuring information asymmetry as *ASC*

Ind. Var.	Dep. Var. = $\ln(I+ASC)$		
	Coef.	T-stat.	Adj. R^2
$\ln(NEWSDAYS)$	-0.053	-4.02	0.296