# Earnings announcements, private information, and liquidity

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## Introduction and summary

Efficient financial markets facilitate the smooth transfer of money from those who save to those with profitable investment opportunities. Such markets generally exhibit high levels of trading volume and widespread market participation. Investors are willing to participate because they are convinced that the prices at which securities can be bought and sold are reasonably efficient. For example, a market participant should be able to buy or sell a share of stock in XYZ company at a price very close to the present discounted value of the market's best estimate of XYZ's future dividend payments.[1]

So where do these market estimates come from? There are two main types of information underlying these estimates—one, information that is common to all market participants (I call this public information), and two, information that is specific to individual investors (I call this private information). An example of public information in this context would be a news release about company XYZ that might be expected to move the company's share price. A company making a surprisingly good earnings announcement typically sees an immediate rise in its stock price. Bad news generally has the reverse effect. Clearly, this type of information impacts market prices.

What is less clear is whether and to what extent private information impacts stock prices. On most trading days, there is no obvious "news" (that is, public information) regarding the value of a particular stock, yet stocks still trade and often show noticeable price changes. Some widely held stocks trade every few seconds on all trading days. Although some of this activity can be linked to public news, much of the trading and related price changes occur when there is no easily observable event or publicly conveyed information believed to be relevant to a given company's stock price. Suppose that an investor places a large order to purchase shares of XYZ on a day when no public news about XYZ is released. Depending on the characteristics of this trade, the price of XYZ may change. For example, if market participants believe this trade was made by an investor who believes the stock is undervalued, others may revise their own expectations and afford shares of XYZ a higher price. Alternatively, participants observing a large purchase order may attribute the purchase to the fact that the given purchaser of XYZ is a manager of an index fund that is well known to have been receiving large inflows of investment capital. Thus, the purchase of XYZ contains no information about the value of XYZ shares. In this case, one might expect the purchase to have a more limited impact on the stock's price. In reality, the underlying purpose of individual trades is not generally known, and therefore one can characterize trades as containing some degree of *private* information.

Understanding how both public and private types of information influence security prices is one of the main goals of financial market microstructure analysis. Earnings announcements are perhaps the most visible form of public information. At the most extreme, insider trading by an executive knowing the contents of a forthcoming news release is an example of private information. However, private information can simply be thought of as all information about a given security price that is not known by all who trade it. For example, a mutual fund manager's decision to reduce

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the holding of a given stock would be considered private information capable of affecting security prices.

Private information, however, can be even less tangible. Differing opinions as to the implications of an earnings announcement may generate important private information, since some may believe the optimal response to the news is to buy a security, whereas others may wish to sell. It is the collective trades of market participants that move prices. Market microstructure analysis presumes that trading is necessary to determine prices because it conveys private information regarding the value of the underlying asset. The intuition is relatively simple: As a sequence of sell orders arrives, prices will be adjusted lower as potential buyers incorporate a higher probability that better informed traders believe the previous price was too high.

This article attempts to shed light on the relative importance of private versus public information in moving security prices. I examine closely the intraday trading activity of ten large companies trading on the New York Stock Exchange and estimate an empirical model that relates trading activity to price changes. My focus is on how this trading–price change relationship changes on days when there is a major release of public information regarding the company in question—in particular, quarterly earnings announcements. In this way, my goal is to quantify by how much, if any, the trading–price change relationship changes with a large increase in public information.

My hypothesis is that the strength of the trading–price change relationship is a measure of the importance of private information in security price formation. An empirical implication of this is that a major release of news should be accompanied by a reduction in the strength of the relationship between trading and price changes. I conduct a series of empirical exercises that provide evidence consistent with this hypothesis. However, my results further indicate that even after an earnings announcement, private information plays a significant role in security price determination. Across the firms in my sample, I find that the strength of the trading–price change relationship, my proxy for the importance of private information, declines by no more than one-third on trading days immediately following a company's quarterly earnings announcement. Thus, private information appears to be a significant factor in the relationship between trading and prices.

The remainder of this article is organized as follows. First, I briefly review some related work. Then, I describe the data and the empirical framework of my analysis. Finally, I present my findings and discuss their implications.

## Related literature

As mentioned previously, market microstructure theory argues that order flow (that is, the sequence of buy and sell orders) affects prices because it conveys private information regarding the value of the underlying asset. In Glosten and Milgrom (1985), for example, the authors formally model why private information leads immediately to the presence of a bid–ask spread (the difference between the proposed purchase price and proposed sale price for the same security) as well as a relationship between trading and price changes. In their model, a marketmaker[2] for a given security stands ready to buy or sell. The marketmaker believes, however, that some of the potential buyers have private information that indicates that the marketmaker's current price of the security is too low. Alternatively, or perhaps in addition, the marketmaker believes that some potential sellers of the security have private information indicating the marketmaker's price is too high. The result of this asymmetry, along with the marketmaker's continued willingness to trade, is a positive bid–ask spread. That is, the price at which a marketmaker is willing to buy is lower than the price at which he is willing to sell. This spread serves as compensation for trades made with those counterparties with superior information.[3] As a sequence of sell orders arrive, marketmakers lower bid prices, incorporating the probability that the order flow implies that better informed investors believe the previous price was too high. This adjustment of posted spreads implies an analogous change in observed transaction prices.

Over the past two decades, the microstructure literature has explored how, when, and how much order flow affects stock prices. Here, I focus on the work most related to my current analysis, specifically work on the relationship between trading and price changes.[4] This relationship ultimately provides a(n inverse) measure of a security's liquidity because a stock whose price changes a lot in response to incoming trades would be deemed relatively illiquid. The literature shows that liquidity itself and the relationship between public news releases and liquidity can be measured in a number of ways.

Seppi (1992) conducts empirical tests to determine the informativeness of block trades (typically, 10,000 shares or more) and how this informativeness correlates with public news releases. In particular, he documents that the prices at which such trades are filled are positively correlated with the earnings surprises. That is, block trades occur at higher prices before positive earnings surprises and at lower prices before negative earnings surprises. This is consistent with the belief that investors making such trades, on average, have some knowledge about the information that will be made public in a subsequent earnings announcement and are therefore anticipating the change in stock price. Lee, Mucklow, and Ready (1993) explicitly describe various alternative measures of market liquidity. They focus not only on the size of the bid–ask spread, but also on a stock's posted depth, which measures the quantity of shares a marketmaker is willing to transact at the posted bid and ask prices. Their study documents that both spreads and depth adjust to the perceived amount of private information in the market. In particular, spreads generally widen and depth generally falls preceding earnings announcements.

Koski and Michaely (2000) extend these findings by examining the relationship between measures of liquidity (for example, spreads and depth) across key information periods, which include both earnings and dividend periods. They find that these liquidity measures do relate to the perceived information content of the trade. In particular, large trades before dividend announcement periods tend to reduce depth and increase spreads most strongly. Similar results, though smaller in magnitude, are found during announcement periods. This is consistent with the notion that private information is at its highest level just prior to a news release. However, since these authors combined information from before and after an announcement period, they could not distinguish precisely how news affects liquidity over the period immediately preceding and following announcements, nor did they formally analyze the trading–price change relationship.

Green (2004) conducts a study of the relationship between announcements and the information content of trading in U.S. Treasury bonds. For Treasury bonds, news announcements are not about corporate earnings, but rather about the latest release of economic data. Green finds that when macroeconomic news is released, the information component of trading increases. Thus, unlike Koski and Michaely (2000), Green associates public news release with an *increase* in private information. Perhaps macroeconomic news releases generate more information on which individual traders can disagree, generating a higher share of private information that in turn affects security prices.

Thus, the previous empirical work provides evidence that the more informative a given trade, the greater its influence on security prices. However, the evidence is somewhat mixed with regard to how the overall liquidity of a security is influenced by news. In particular, there is not yet a consensus as to whether public news arrival reduces or generates private information. Rather, it appears from previous work that public news releases have the potential either to generate or eliminate private information. Thus, it remains an empirical question to decide whether public news arrival will strengthen the trading–price change relationship (consistent with private information generation) or weaken it (consistent with private information elimination).

## Data and empirical framework

My analysis relies on data from three sources. I begin with the universe of firms whose earnings history was available on Briefing.com. To select my sample, I required that Briefing.com reported the date, time, value, and market expectation of every earnings announcement that a firm reported between January 29, 2001, and December 31, 2004. For my purposes, the Briefing.com data provide an important piece of information unavailable in the more traditionally used sources of announcement histories, such as Thomson Financial's FirstCall and the Institutional Brokers' Estimate System: whether a firm's earnings announcement was made prior to the stock market opening, during the trading day, or after the market close. Thus, it is possible to know precisely which day of stock market trading is associated with the reaction to the earnings announcement. This distinction will be crucial to my analysis. In what follows, I refer to the first trading day following the announcement as a company's "announcement day." For example, if a company announces its earnings on a Tuesday before or during trading hours, its announcement day is that Tuesday. If the announcement is made on a Tuesday after the market closes, its announcement day will be that Wednesday. Furthermore, my analysis carefully considered the role of weekends and public holidays in order to correctly pair a given announcement with the next possible trading day.

I then compared this sample of firms to the database provided by the Center for Research in Security Prices. I considered only those firms that were listed on the New York Stock Exchange (NYSE) to avoid the well-known differences in the liquidity (and by extension, the strength of the trading–price change relationship) of stocks trading on different exchanges. I then calculated each firm's market capitalization based on stock price data as of December 31, 2001, and selected the ten largest remaining firms to be the focus of my study.

Having identified the ten stocks in my sample, I then combined the earnings announcement information from Briefing.com with high frequency data on the trading of the stocks of these ten firms from the NYSE Trade and Quote (TAQ) database. Although Briefing.com provides earnings information since

**TABLE 1**

**Summary statistics**

| Name/Ticker | Average trade size, shares | Average number of trades | Average bid–ask spread, dollars | Average depth, round lots |
|---|---|---|---|---|
| Bristol-Myers Squibb Co. (BMY) | 1,537.9490 | 4,175.6380 | 0.0334 | 31.6022 |
| | (527.6960) | (1,326.6590) | (0.0238) | (14.9068) |
| EMC Corp. (EMC) | 2,343.7580 | 7,070.8470 | 0.0331 | 79.0106 |
| | (655.9954) | (2,606.1300) | (0.0375) | (36.9236) |
| General Electric Co. (GE) | 2,040.1440 | 11,271.3300 | 0.0271 | 68.7537 |
| | (703.1345) | (3,437.3040) | (0.0156) | (40.4598) |
| Home Depot Inc. (HD) | 1,339.4020 | 6,446.9410 | 0.0304 | 36.5258 |
| | (339.1715) | (2,160.3100) | (0.0178) | (20.9643) |
| International Business Machines Corp. (IBM) | 1,100.4560 | 6,776.2480 | 0.0523 | 16.3487 |
| | (384.0330) | (1,680.0090) | (0.0302) | (8.0540) |
| Coca-Cola Co. (KO) | 1,415.3070 | 3,827.4650 | 0.0290 | 23.3063 |
| | (473.8881) | (1,321.2770) | (0.0149) | (10.2120) |
| Merck & Co. Inc. (MRK) | 1,403.8030 | 5,421.9910 | 0.0382 | 26.9202 |
| | (448.6887) | (3,776.4130) | (0.0258) | (22.3486) |
| Nortel Networks Corp. (NT) | 4,906.4550 | 5,451.2300 | 0.0182 | 720.4567 |
| | (3099.6320) | (3,899.5310) | (0.0170) | (730.3201) |
| Pfizer Inc. (PFE) | 1,982.2700 | 8,839.0240 | 0.0270 | 55.0667 |
| | (465.7550) | (3,908.9970) | (0.0152) | (38.1269) |
| SBC Communications Inc. (SBC) | 1,784.0950 | 4,608.6720 | 0.0282 | 40.3322 |
| | (516.5796) | (1,219.6850) | (0.0162) | (19.2419) |

Notes: This table reports the mean (and standard deviation in parentheses) of various measures of trading activity for each stock in the sample. Averages are taken across all 959 days that are not within one day of an earnings announcement.
Sources: Author's calculations based on data from Briefing.com and the New York Stock Exchange Trade and Quote database.

1997, I restrict my sample period to January 29, 2001, through December 31, 2004. The starting date of my sample corresponds to the first day on which all stocks listed on the NYSE began trading with a minimum price increment (tick) of one cent (that is, decimalization). This eliminates the need to consider how minimum tick size changes might influence the relationship between earnings announcements and liquidity, since a vast literature has documented the importance of minimum tick size to liquidity in general.

I then adjusted the data according to procedures common in the microstructure literature. I dropped quotes with obviously erroneous data (for example, quotes with bid or ask prices equal to zero or quotes with bid–ask spreads dramatically different from the previous or subsequent quote). Following Hasbrouck (1991), I kept only quotes originating from the NYSE and considered multiple trades on a regional exchange for the same stock at the same price and time as one trade. Then, I sorted the trade data (for each company and day) by time, with the prevailing quote at transaction $t$ defined as the last quote that was posted at least five seconds before the transaction (Lee and Ready, 1991). I provide a complete listing of the stocks in my sample, along with summary statistics on their trading, in table 1.

The summary statistics show many facts about stock market trading. First, these ten stocks are very heavily traded. The least actively traded stock in my sample is Coca-Cola (KO), yet shares of this stock traded over 3,800 times each day, a trading intensity of roughly once every six seconds. The most actively traded stock in my sample is General Electric (GE), whose shares traded over 11,000 times each day on average (approximately once every two seconds). Bid–ask spreads on all of the sample stocks are typically quite narrow. On average, spreads range from a low of 1.82 cents for Nortel (NT) to a high of 5.23 cents for IBM.

I am interested in changes in trading characteristics that occur on or around earnings announcement days. To present some preliminary evidence on this subject, I regress the daily values of various measures of trading activity on a set of dummy variables that indicate the day before, the day of, and the day after an earnings announcement. Coefficients from this regression, which represent differences relative to all other days, are presented in table 2. This table indicates that there are noticeable changes in common proxies for stock market liquidity on earnings announcement days. Most strikingly, trading volume increases. Trade size and average depth, which represents the number of shares available at the posted spread, also tend to rise on announcement days, although these results appear to be statistically significant for only a subset of my sample firms. For KO shares, for example, average trade size increases by 587 shares, and typical depth rises by 7.4 round lots (that is, 740 shares) on announcement days. Not all statistical indicators of liquidity, however, indicate greater liquidity on announcement days. Although not statistically significant in most cases, bid–ask spreads tend to rise on announcement days. For instance, IBM's bid–ask spread typically increases by 1.4 cents on an announcement day. Data across these ten stocks tell a similarly inconsistent story with regard to the relationship between liquidity and announcement days—namely, that announcement days witness an increase in trading volume and depth, but either little change or a widening of bid–ask spreads.

Because announcement days are correlated with heavier trading volume and higher depth but wider spreads, it would be useful to focus on a measure of stock market liquidity that may account for these changes. Here, I use the price impact of a trade as a measure of a stock's liquidity that embeds the impact of volume, spreads, and depth. That is, I take the position that price impact is the quantity that ultimately relates to the strength of the trading–price change relationship and that volume, spreads, and depth (among other observable characteristics) are noisy indicators of such a relationship.

I adopt the general empirical framework of Hasbrouck (1991), who estimates a vector autoregression (VAR) model of two equations. The first equation models trade-to-trade stock returns as a function of past returns as well as current and past trades, explicitly considering whether the trade was to purchase or to sell shares. The second equation models the decision to buy or sell as a function of both past trading and past stock returns. In such a framework, Hasbrouck delivered some benchmark results upon which I build in my analysis. In particular, Hasbrouck documents the positive relationship between order flow and price changes using a sample of 80 NYSE and American Stock and Options Exchange (AMEX) stocks. That is, buy orders lead to price increases, and sell orders lead to price declines. Hasbrouck further extended his analysis to indicate that larger trades tend to move prices more, a finding that I incorporate into my framework.

My empirical results are based upon VAR models of increasing complexity. The first merely replicates a version of the Hasbrouck (1991) analysis. I specify this by equations 1 and 2, which I estimate separately for each of the ten firms in my sample.

$$1)\quad r_t = \sum_{i=1}^{L} a_i^r r_{t-i} + \sum_{i=0}^{L} \gamma_i^r x_{t-i} + \nu_{rt},$$

$$2)\quad x_t = \sum_{i=1}^{L} a_i^x r_{t-i} + \sum_{i=1}^{L} \gamma_i^x x_{t-i} + \nu_{xt}.$$

The unit of observation is the trade, which is indexed by the subscript $t$. The variable $r_t$ is defined as the change in the natural logarithm of the midquote (average of the current bid and ask price) of a given stock that follows the trade at time $t$. I use midquotes as my price variable to eliminate the well-known problems with using actual transaction prices in empirical analysis, notably the tendency of transaction prices to bounce between the bid and ask prices without indicating any true movement in the underlying security value. Also following Hasbrouck (1991), I define $x_t$ as the log of the number of shares of trade $t$, signed to indicate whether or not trade $t$ was initiated by a buy order or a sell order. That is, a positive value of $x_t$ indicates a buyer-initiated trade, and a negative value indicates a seller-initiated trade. As the TAQ data do not indicate which party initiated each trade, I follow the literature's convention and assume that trades at a transaction price greater than the midquote were buyer-initiated and trades below the midquote were seller-initiated. For trades at the midquote, I determine the side of trade origination according to the tick rule (see Lee and Ready, 1991).

I truncate the VAR model by setting $L$ equal to eight for all stocks and for all time periods. Though longer than the five lags adopted by Hasbrouck (1991), this reflects the higher level of trading in more recent periods. Finally, I estimate equations 1 and 2 by ordinary least squares and correct standard errors using White's (1980) methodology.

I then expand the model in several ways to explore how the relationship between trading and price might change in ways related to earnings announcements. My first additional model can be expressed by equations 3 and 4.

**TABLE 2**

**Deviations around announcement dates**

| Name/Ticker | Average trade size, shares | Average number of trades | Average bid–ask spread, dollars | Average depth, round lots |
|---|---|---|---|---|
| Bristol-Myers Squibb Co. (BMY) | | | | |
| Day before announcement | 72.634 | 28.562 | –0.005 | –3.274 |
| | (105.172) | (257.771) | (0.004) | (2.716) |
| Day of announcement | 565.982 | 1,484.962 | 0.003 | 4.404 |
| | (144.990)** | (527.086)** | (0.004) | (3.835) |
| Day after announcement | 266.810 | 615.362 | –0.000 | –0.466 |
| | (155.257) | (296.985)* | (0.005) | (2.896) |
| EMC Corp. (EMC) | | | | |
| Day before announcement | 243.296 | 668.353 | –0.002 | 9.878 |
| | (158.294) | (840.003) | (0.010) | (10.834) |
| Day of announcement | 735.740 | 2,981.953 | 0.003 | 40.342 |
| | (176.647)** | (947.399)** | (0.009) | (11.384)** |
| Day after announcement | 353.466 | 476.953 | –0.003 | 15.625 |
| | (158.172)* | (614.181) | (0.009) | (8.527) |
| General Electric Co. (GE) | | | | |
| Day before announcement | 97.373 | 1,056.405 | 0.000 | –0.966 |
| | (133.625) | (1,076.020) | (0.003) | (4.692) |
| Day of announcement | 129.556 | 4,079.672 | 0.001 | 12.941 |
| | (100.314) | (1,441.108)** | (0.003) | (10.381) |
| Day after announcement | –192.732 | 1,288.405 | –0.001 | –0.772 |
| | (102.162) | (1,190.934) | (0.003) | (7.713) |
| Home Depot Inc. (HD) | | | | |
| Day before announcement | 48.028 | 1,261.246 | –0.001 | 0.163 |
| | (70.942) | (720.627) | (0.003) | (3.166) |
| Day of announcement | 375.450 | 4,809.309 | 0.013 | 18.399 |
| | (86.186)** | (1,315.088)** | (0.005)** | (6.817)** |
| Day after announcement | 219.703 | 2,343.559 | –0.000 | 6.231 |
| | (96.178)* | (913.464)* | (0.003) | (3.282) |
| International Business Machines Corp. (IBM) | | | | |
| Day before announcement | 170.724 | 1,727.752 | 0.004 | 1.907 |
| | (104.526) | (380.877)** | (0.008) | (1.826) |
| Day of announcement | 626.777 | 2,918.418 | 0.014 | 3.711 |
| | (117.181)** | (509.751)** | (0.006)* | (1.689)* |
| Day after announcement | 213.212 | 596.018 | –0.004 | 1.969 |
| | (98.206)* | (349.537) | (0.005) | (1.967) |
| Coca-Cola Co. (KO) | | | | |
| Day before announcement | 78.408 | –48.028 | –0.000 | 1.610 |
| | (74.701) | (274.959) | (0.003) | (1.895) |
| Day of announcement | 587.421 | 1,125.597 | 0.008 | 7.404 |
| | (104.822)** | (584.509) | (0.004) | (3.442)* |
| Day after announcement | 431.017 | 202.347 | 0.003 | 1.503 |
| | (157.521)** | (365.853) | (0.003) | (1.675) |

**TABLE 2 (CONT.)**

**Deviations around announcement dates**

| Name/Ticker | Average trade size, shares | Average number of trades | Average bid–ask spread, dollars | Average depth, round lots |
|---|---|---|---|---|
| Merck & Co. Inc. (MRK) | | | | |
| Day before announcement | 175.166 | –312.124 | –0.003 | 2.818 |
| | (103.951) | (566.237) | (0.005) | (6.171) |
| Day of announcement | 368.051 | 769.009 | 0.009 | 3.516 |
| | (179.600)* | (743.123) | (0.010) | (4.235) |
| Day after announcement | 141.529 | 521.743 | –0.003 | 0.014 |
| | (112.102) | (610.989) | (0.004) | (3.631) |
| Nortel Networks Corp. (NT) | | | | |
| Day before announcement | 820.685 | 518.699 | –0.002 | 339.403 |
| | (767.880) | (943.700) | (0.002) | (347.604) |
| Day of announcement | 4,894.836 | 2,287.913 | –0.001 | 377.644 |
| | (3,370.319) | (1,918.236) | (0.002) | (314.681) |
| Day after announcement | 514.354 | 570.556 | –0.003 | 80.856 |
| | (698.632) | (1,366.929) | (0.002) | (214.662) |
| Pfizer Inc. (PFE) | | | | |
| Day before announcement | –143.558 | 154.976 | –0.003 | –6.791 |
| | (58.216)* | (531.356) | (0.002) | (5.924) |
| Day of announcement | 357.292 | 2,769.176 | 0.001 | 21.312 |
| | (219.192) | (1,017.787)** | (0.003) | (16.608) |
| Day after announcement | 198.882 | 1,007.643 | –0.003 | 9.601 |
| | (156.403) | (581.881) | (0.002) | (13.909) |
| SBC Communications Inc. (SBC) | | | | |
| Day before announcement | 315.454 | 358.595 | –0.001 | 5.006 |
| | (141.799)* | (350.205) | (0.003) | (7.154) |
| Day of announcement | 751.766 | 1,028.662 | 0.002 | 9.746 |
| | (109.573)** | (432.073)* | (0.003) | (6.838) |
| Day after announcement | 533.909 | 682.195 | –0.000 | 6.627 |
| | (146.305)** | (350.751) | (0.003) | (4.980) |

*Significant at the 5 percent level.
**Significant at the 1 percent level.
Note: This table reports the coefficient estimates (and the Newey-West standard errors in parentheses) of a regression of average daily values of each stock on the days surrounding an announcement date.
Sources: Author's calculations based on data from Briefing.com and the New York Stock Exchange Trade and Quote database.

$$3)\quad r_t = \sum_{i=1}^{L} a_i^r r_{t-i} + \sum_{i=0}^{L}\left(\gamma_i^r + \theta_i^r a_{t-i}\right)x_{t-i} + \nu_{rt},$$

$$4)\quad x_t = \sum_{i=1}^{L} a_i^x r_{t-i} + \sum_{i=1}^{L}\left(\gamma_i^x + \theta_i^x a_{t-i}\right)x_{t-i} + \nu_{xt}.$$

In this empirical specification, I add terms to the model that interact the trade size variable $x_t$ with a dummy variable $a_t$, which is set equal to one if trade $t$ occurs on an announcement date. This allows the relationship between trading and price changes to be different on announcement days. For example, positive estimated values for θ would indicate that the relationship between trading and stock returns becomes stronger on announcement days.

Because I have identified a positive relationship between trading volume and announcement days, it is important to confirm that any relationship I find between announcement days and price impact when I estimate equations 3 and 4 is due to the announcement and not simply an artifact of higher trading volume. To this end, I next estimate an expanded version of equations 3 and 4, where I interact the trade indicator variable with a variable $l_t$, measuring trading volume on the day on which trade $t$ occurs. This expanded specification is shown in equations 5 and 6.

$$5)\quad r_t = \sum_{i=1}^{L} a_i^r r_{t-i} + \sum_{i=0}^{L} \left(\gamma_i^r + \theta_i^r a_{t-i} + \kappa_i^r l_{t-i}\right) x_{t-i} + \nu_{rt},$$

$$6)\quad x_t = \sum_{i=1}^{L} a_i^x r_{t-i} + \sum_{i=1}^{L} \left(\gamma_i^x + \theta_i^x a_{t-i} + \kappa_i^x l_{t-i}\right) x_{t-i} + \nu_{xt}.$$

My next empirical specification extends the model described by equations 5 and 6 to explore whether days immediately surrounding announcement days may be noticeably different than other days. As described in equations 7 and 8, I do this by interacting variables $b_t$, defined to equal one if trade $t$ occurs on the day before an announcement date and zero otherwise, and $f_t$, defined analogously for the day after an announcement date, with the trade size variable $x_t$, as follows:

$$7)\quad r_t = \sum_{i=1}^{L} a_i^r r_{t-i} + \sum_{i=0}^{L} \left(\gamma_i^r + \lambda_i^r b_{t-i} + \theta_i^r a_{t-i} + \phi_i^r f_{t-i} + \kappa_i^r l_{t-i}\right) x_{t-i} + \nu_{rt},$$

$$8)\quad x_t = \sum_{i=1}^{L} a_i^x r_{t-i} + \sum_{i=1}^{L} \left(\gamma_i^x + \lambda_i^x b_{t-i} + \theta_i^x a_{t-i} + \phi_i^x f_{t-i} + \kappa_i^x l_{t-i}\right) x_{t-i} + \nu_{xt}.$$

I estimate the empirical model described by equations 7 and 8 to explore whether the private information content of a trade varies according to the proximity to a public announcement rather than only depending on whether the announcement was just made. For example, one might believe that if announcement days reduce the private information content of stock trading, then the day before such an announcement might be expected to contain a higher than average amount of private information. That is, the likelihood of a trader's having private information regarding a future earnings announcement might be expected to be the greatest immediately before the announcement. If this were the case, one might expect that the $\lambda_i$ coefficients would be greater than zero. As for the day following the announcement, allowing the relationship between trading and stock returns to differ facilitates an exploration as to whether any changes detected on the announcement day persist until the following day. To the extent that there is persistence, one might expect to estimate values for $\theta_i$ very close to the values estimated for $\phi_i$.

Much like equations 7 and 8, my final empirical specification extends the model described by 5 and 6. However, rather than exploring whether the relationship between trading and returns varies according to the proximity in calendar time from the announcement date, I instead explore whether the importance of the announcement date varies according to the realized content of the given announcement. That is, I wish to distinguish between announcements that contain surprising information and those that do not. In particular, I estimate the model described by equations 9 and 10,

$$9)\quad r_t = \sum_{i=1}^{L} a_i^r r_{t-i} + \sum_{i=0}^{L} \left(\gamma_i^r + \theta_i^r a_{t-i} + \beta_i^r a_{t-i} s_{t-i} + \kappa_i^r l_{t-i}\right) x_{t-i} + \nu_{rt},$$

$$10)\quad x_t = \sum_{i=1}^{L} a_i^x r_{t-i} + \sum_{i=1}^{L} \left(\gamma_i^x + \theta_i^x a_{t-i} + \beta_i^x a_{t-i} s_{t-i} + \kappa_i^x l_{t-i}\right) x_{t-i} + \nu_{xt}.$$

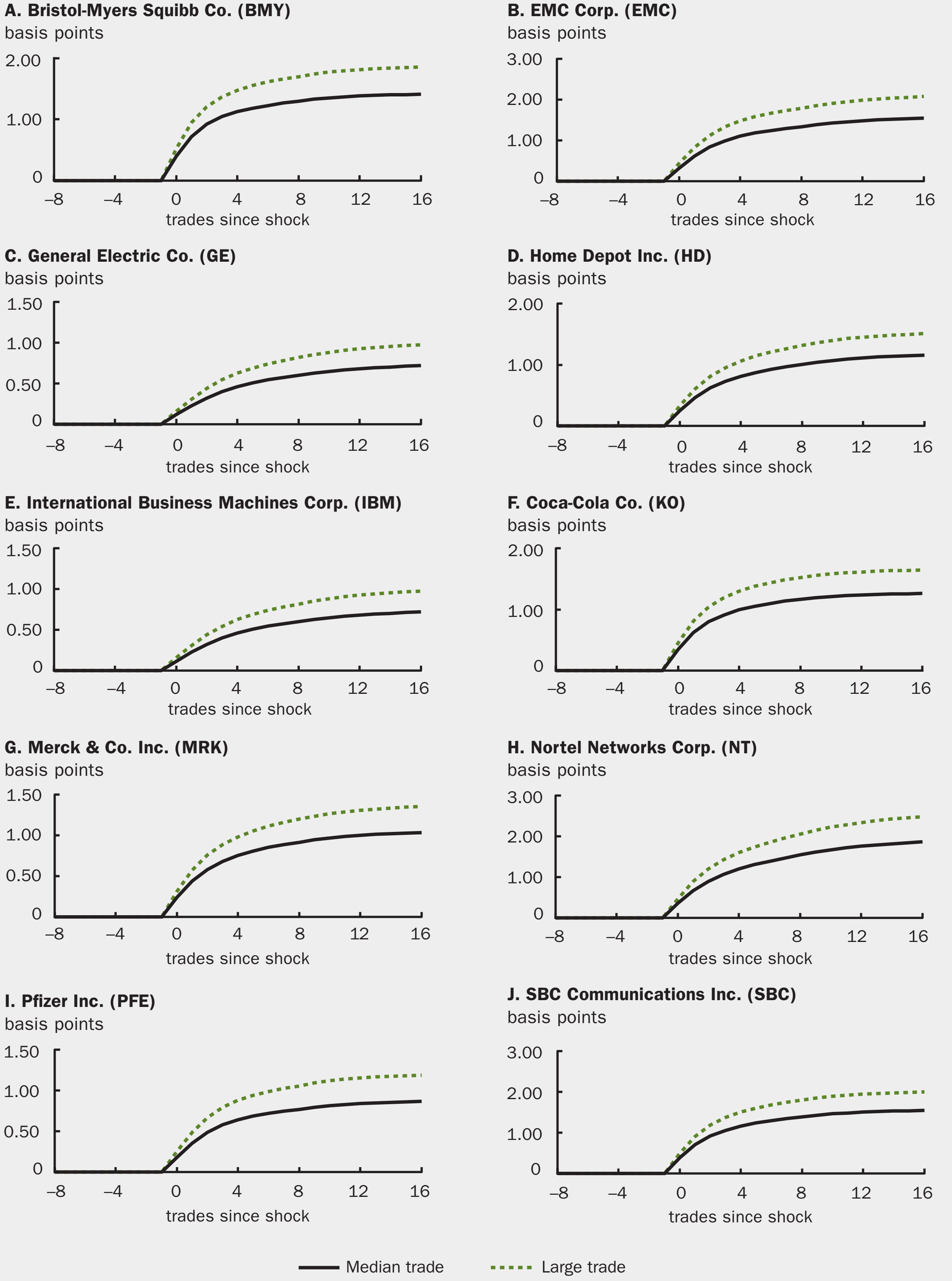
Here, I define $s_t$ as an indicator variable that is equal to one when the actual earnings announced differed from expected earnings as reported by Briefing.com by more than \$0.01 per share.[5] One hypothesis is that surprising earnings releases reveal more private information than those that are unsurprising. If this were true, one would expect the coefficients $\beta_i$ to be negative.

## Empirical results

I form my estimate of the price impact of a trade by calculating the cumulative impulse response of a shock to $x_t$ on stock returns $r_t$. As a point of departure, figure 1 graphs these responses for each firm, when the size of the shock $x_t$ is set equal to each stock's median trade size and also to the stock's 90th percentile trade size. This allows one to judge the overall liquidity of a stock on average across the roughly four years of data and to measure by how much more a large trade moves prices than a more typical trade. For example, panel A of figure 1 depicts the impulse response functions for Bristol-Myers Squibb Co. (BMY). The graph shows that a median-sized buy order is estimated to eventually raise the price of BMY shares by approximately 1.4 basis points. A large trade that was unexpected is estimated to have a long-run impact of increasing BMY share prices by a little over 1.8 basis points. The main findings illustrated by figure 1 are that even across a sample of large firms, market liquidity varies across firms and across trades of a given firm. For instance, across these ten stocks, a median-sized trade is estimated to raise prices by between 0.7 and 1.9 basis points, depending on the

**FIGURE 1**

**The long-run price impact of median- and large-sized trades**




Sources: Author's calculations based on data from Briefing.com and the New York Stock Exchange Trade and Quote database.

stock. Furthermore, for every stock in the sample, larger trades appear to have a greater price impact.

As illustrated in figure 1, the cumulative impulse response of a trade shock on stock returns generally begins with a rapid increase immediately following the shock and then levels off at a point higher than its initial value. As I extend the initial model to account for announcement days, this shape remains. Because of this, I choose to present the remaining results by reporting values based on the "long-run" impulse response, which is derived from the cumulative impulse response function by reading off the final value calculated—in this case, the value of the cumulative shock to returns seen 16 trades after the initial shock. Note that this long run typically takes less than a minute. To illustrate, figure 2 reports the cumulative long-run impulse responses on returns of a trade shock for each of the ten stocks in my sample after I estimate equations 3 and 4, which extend the previous model by allowing the price impact of a trade to vary according to whether the given trade occurs on a day with an earnings announcement. Each panel of figure 2 reports two values. The first bar reports the long-run price impact of a median-sized trade on a nonannouncement day (that is, normal day). The second bar reports the long-run cumulative value of the same sized trade on an announcement date.

Qualitatively, the results are similar across all ten firms in the sample. In particular, the price impact of a median-sized trade is uniformly lower on an announcement day than on other days during the sample period. This result is consistent with the notion that price impact is partially explained by marketmakers defending themselves against asymmetric information. In other words, prices move in response to trades because marketmakers believe some traders have private information. Furthermore, this private information is reduced when a public earnings announcement is released. The magnitude of the reduction in price impact varies across the ten firms. In the case of BMY, the reduction in price impact is rather small. My model estimates that the long-run price impact of a trade declines from approximately 1.42 basis points to 1.39 basis points, a reduction of only 2.1 percent. For other companies, the reduction in price impact on announcement days is far more pronounced. The impact of a median-sized trade of Home Depot (HD) stock is roughly 1.2 basis points on nonannouncement days, but only 0.8 basis points on announcement days. This represents a reduction in price impact of 33 percent.

The results of figure 2 show that announcement days witness a decline in the price impact of trading, suggesting that the release of public information does reduce the private information embedded in a trade. I reached this conclusion by estimating a model that allowed the relationship between trading and returns to vary according to whether a given trade occurred on an announcement day. As mentioned previously, it is important to attribute the lower price impact of a trade on announcement days to the announcement and not to the typically higher trading volume witnessed on announcement days. Figure 3 reports the analogous results to those of figure 2, only with the long-run price impact measures being derived from an estimation of equations 5 and 6, which control for daily trading volume.[6] As shown in figure 3, for nine out of ten stocks, announcement days remain correlated with a reduction in the long-run price impact of a trade. Moreover, the one stock for which this result is not found is BMY, which had a negligible decline in price impact when I did not control for trading volume. The magnitude of the decline is also largely comparable to what was reported in figure 2. The impact of a median-sized trade of Home Depot (HD) stock on a day with typical trading volume, for example, is estimated to be 0.93 basis points on nonannouncement days, but only 0.62 basis points on announcement days. This represents the same 33 percent reduction in price impact for HD that was reported in figure 2.

Next, I analyze my extensions to this basic framework. One extension is to explore whether the private information that does get released in an earnings announcement may partially "leak" to the public before the official release or, alternatively, whether the private information is at a maximum before the release. A related question is how the private information component of price impact varies after the announcement date. For example, does the relationship between trading and returns immediately revert to a more normal level or does price impact remain at a lower level for some time following the earnings release?

Figure 4 (p. 51) addresses these questions by reporting the cumulative long-run price impact for a median-sized trade, calculated from an analysis using equations 7 and 8. Recall that in this model specification, the relationship between trading and returns is allowed to vary not only on an announcement day, but also on the day before and the day after an announcement. To illustrate the information contained in figure 4, I highlight the results for shares of Nortel Networks Corp. (NT). The first bar in panel H reports that the cumulative long-run impact of a median-sized trade of NT stock is 1.6 basis points on a day not in proximity to an earnings announcement. The second through fourth bars calculate the same quantity only on the day of, the day before, and the day after an

**FIGURE 2**

**The long-run price impact of a trade on normal days and announcement days**


Sources: Author's calculations based on data from Briefing.com and the New York Stock Exchange Trade and Quote database.

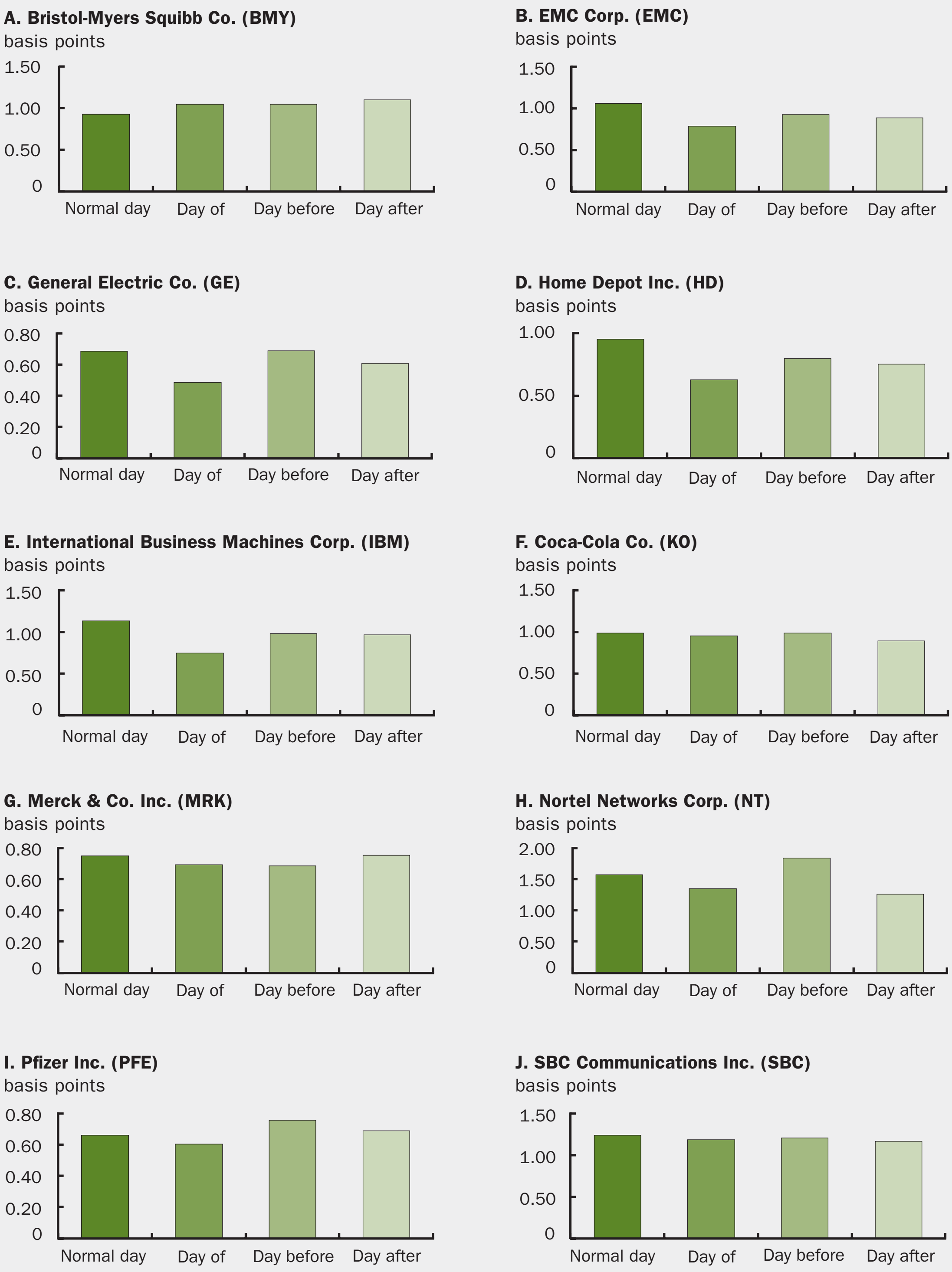
**FIGURE 3**

**The long-run price impact of a trade on normal days and announcement days, controlling for changes in trading volume**


Sources: Author's calculations based on data from Briefing.com and the New York Stock Exchange Trade and Quote database.

**FIGURE 4**

**The long-run price impact of a trade before, during, and after announcements, controlling for changes in trading volume**




Sources: Author's calculations based on data from Briefing.com and the New York Stock Exchange Trade and Quote database.

earnings announcement. As reported in the second bar, the price impact of a trade of NT falls to around 1.3 basis points on an announcement day. However, the figure also indicates that the price impact remains near this lower level on the following day. On the day before the announcement, however, the price impact of an NT trade is higher than is typical, measuring approximately 1.8 basis points.

This pattern is consistent with the following story of the private information content of price impact. Suppose that every day new information about the value of NT shares is generated, but initially, this new information is private. Suppose further that none of this private information is released until the day of the announcement. In this scenario, one expects that the amount of private information is greatest just before the announcement. According to microstructure theory, this would then cause the price impact of a trade to be greatest just before an announcement and to fall after an announcement. This story is therefore consistent with the estimated price impact of NT trading around announcement dates. Four of the ten sample stocks, however, are estimated to have a greater price impact on the day before an earnings announcement, and so this story is potentially an explanation for only some firms.

Consider a different case such as the one illustrated by the results for trading of IBM stock. The long-run price impact of a trade of IBM is lower on days immediately before and immediately after an earnings announcement than it is on other days. Five of the ten stocks match this pattern. If private information was the source of the change in price impact, then these results suggest that private information is reduced *before* the announcement date. This would be consistent with a potential information leak or perhaps with information being intentionally released by the company prior to its formal quarter earnings release.

One final issue I explore is whether the reduction in price impact observed on announcement days is related to what news is actually released in the announcement. For example, an earnings release that is in line with market expectations may not reduce private information very much, since even in the absence of a formal announcement, market participants seemed quite knowledgeable about the announcement's contents. A surprising announcement, however, may reveal a greater amount of private information. An alternative hypothesis is that a surprising announcement may *generate* more private information because there may be more differences in opinion as to the implication of an earnings *surprise* on the fundamental value of the stock.

I explore the relationship between price impact and announcement content by estimating equations 9 and 10, which allow the trading and return relationship to vary according to whether a trade occurs on an announcement date and whether the given announcement is surprising. I define a surprising announcement as one in which the market's expected earnings were more than $0.01 per share away from the actual reported value. For nine of the ten firms in the sample, this identified roughly half of all announcements as surprises. The tenth firm, General Electric Co. (GE), did not have a surprising announcement over the entire sample period, with earnings never being more than a penny away from the market's expectation. For this reason, I do not include GE in this final empirical estimation.

Figure 5 presents the long-run price impact of a median-sized trade of each of the remaining nine companies. As is illustrated in the figure, there does not appear to be a general relationship between private information content and announcement surprise content. In particular, a trade of six of the nine stocks is associated with a lower price impact when the announcement is more surprising relative to when it is not. For instance, a median-sized trade of Pfizer Inc. (PFE) stock typically moves the price by 0.66 basis points. On a day when an unsurprising announcement is made, price impact falls to 0.62 basis points. On a day when the earnings announcement is also more than a penny away from the market's expectation, price impact falls by even more, to 0.51 basis points. The evidence from the remaining three stocks indicates the opposite relationship between announcement content and price impact reduction. For instance, a trade in the stock of SBC Communications Inc. (SBC) typically moves the share price by 1.23 basis points. This falls to 1.14 basis points on an announcement day without an earnings surprise, but falls by less than 0.01 basis points on announcement days when earnings miss expectations by more than $0.01.

## Conclusion

In this article, I examine how the price impact of a trade varies throughout the days surrounding public earnings announcements. My results indicate that public news releases correlate with a reduction in the price impact of a trade. This finding is consistent with earnings releases generally reducing the asymmetric information component of stock trading. Moreover, this result is robust to the typical increase in trading volume generally observed on such days. Extending the sample beyond a focus on the announcement day alone, however, fails to uncover systematic relationships on either the day before or the day after earnings announcements. In particular, the reduction in price

**FIGURE 5**

**The long-run price impact of a trade for surprising and unsurprising announcements, controlling for changes in trading volume**


Notes: Results for General Electric Co. (GE) are not applicable. See the text for further details.
Sources: Author's calculations based on data from Briefing.com and the New York Stock Exchange Trade and Quote database.

impact on announcement days does not typically persist beyond one trading day, nor do markets seem to contain higher than average levels of asymmetric information on the day prior to anticipated announcements. Perhaps most surprisingly, I do not find a predictable relationship between the change in price impact and the information content of the announcement. For some firms, surprising announcements tend to increase asymmetric information and price impact relative to unsurprising announcements, whereas for other firms the reverse is true.

## NOTES

[1]More generally, the price of a share of stock should equal the present value of future dividends discounted at a rate commensurate with the risk of the given payment stream, where risk is measured by an asset pricing model. Thus, expectations about both future dividends and future risk are relevant in determining current market prices.

[2]A marketmaker is an individual or firm authorized by the stock exchange to buy and sell a particular security with an objective to provide trading liquidity for the security. Generally, a marketmaker is obliged to announce buying and selling prices for a particular security at a particular time.

[3]An implication of this model is that traders lacking private information face higher trading costs in that they must compensate the marketmaker for being willing to transact at posted prices in the presence of those with more information.

[4]Readers who are more interested may wish to begin a more in-depth review of market microstructure analysis by reading Biais, Glosten, and Spatt (2005).

[5]Briefing.com reports earnings expectations from Zacks Investment Research and from Reuters. As it is more complete, I choose the expectation reported by Zacks, but use Reuters data when Zacks data are missing.

[6]For these calculations, trading volume is set to a stock's median (across days in the sample) daily trading volume. Regression results indicate a strong negative relationship between trading volume and price impact. That is, days with higher trading volume are associated with lower price impact of a single trade.

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