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# Driven to Distraction:
# Extraneous Events
# and Underreaction to Earnings News

**Abstract**

Psychological evidence indicates that it is hard to process multiple stimuli and perform multiple tasks at the same time. This paper tests the *investor distraction hypothesis*, which holds that the arrival of extraneous news causes trading and market prices to react sluggishly to relevant news about a firm. Our test focuses on the competition for investor attention between a firm's earnings announcements and the earnings announcements of other firms. We find that the immediate stock price and volume reaction to a firm's earnings surprise is weaker, and post-earnings announcement drift is stronger, when a greater number of earnings announcements by other firms are made on the same day. Distracting news has a stronger effect on firms that receive positive than negative earnings surprises. Industry-unrelated news has a stronger distracting effect than related news. A trading strategy that exploits post-earnings announcement drift is unprofitable for announcements made on days with little competing news.

[Attention] is the taking possession by the mind in clear and vivid form, of one out of what seem several simultaneously possible objects or trains of thought...It implies withdrawal from some things in order to deal effectively with others.

William James, *Principles of Psychology*, 1890

Almost a quarter of British motorists admit they have been so distracted by roadside billboards of semi-naked models that they have dangerously veered out of their lanes.

Reuters (London), November 21, 2005

# 1 Introduction

Since minds are finite, attention must be allocated selectively. When individuals try to process multiple information sources or perform multiple tasks simultaneously, performance suffers.[1] Indeed, conscious thought requires a focus on particular ideas or information to the exclusion of others.

These elemental facts suggest that limited attention affects the perceptions and behavior of investors. Specifically, an investor's effort to understand the implications of a news announcement by one firm for that firm may interfere with the processing of information about another firm arriving at the same time. Although there is recent empirical research on the effects of limited investor attention on securities prices, this basic prediction has not to our knowledge been tested.

A recent theoretical literature models how constraints on processing multiple information signals affects beliefs perceptions and security market prices.[2] These models imply that investor neglect of information signals can lead to serial correlation in asset return volatility (Peng, Xiong, and Bollerslev (2006)), mispricing that is related to publicly available accounting information (Hirshleifer and Teoh (2003)), excessive asset price comovement (Peng and Xiong (2006)), faster rate of incorporation of information by large than by small stocks (Peng (2005)), and neglect of long-term public information (DellaVigna and Pollet (2007)). There has also been analysis of how firms can exploit limited investor attention by disclosing bad news at times when other firms are making

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[1]See, e.g., Kahneman (1973), Riley and Roitblat (1978), Pashler (1998); Baddeley (1990) reviews interference effects in the recall of stored information.

[2]Research that examines the effects of limited attention on individual decisions such as trading include Sims (2003), Gabaix, Laibson, Moloche, and Weinberg (2006), and Gabaix and Laibson (2004).

salient disclosures (Hirshleifer, Lim, and Teoh (2004)), or on days of the week when investors are less attentive (DellaVigna and Pollet (2006)).

In the models of DellaVigna and Pollet (2006) and Hirshleifer and Teoh (2005), investors are risk averse, and a subset neglect the information contained in a firm's latest earnings realization about future profitability. In equilibrium stock prices underreact to earnings surprises, so that prices are on average too low after favorable surprises and too high after unfavorable surprises. In consequence, positive surprises predict high subsequent returns and negative surprises predict low subsequent returns. In other words, there is post-earnings announcement drift, as documented by Bernard and Thomas (1989).

A further empirical implication of these models is that when the amount of attention investors direct toward a firm decreases, there should be more severe underreaction to its earnings surprises, intensifying subsequent drift. We argue here that the amount of attention toward a given firm is likely to be smaller when there are more extraneous news events distracting investors from that firm.[3] Therefore, greater distraction implies more severe underreaction to the firm's earnings news – a weaker immediate reaction to the earnings surprise, and stronger post-earnings announcement drift. Intuitively, we also expect that the greater the distraction, the weaker the trading volume response to a news announcement.

Together, we call these predictions the *investor distraction hypothesis.* In this paper we test the investor distraction hypothesis by measuring when a greater number of public disclosures by other firms compete for investor attention; and whether greater distraction reduces volume of trade.

For at least two reasons, the stock market's processing of a firm's earnings announcements provides an attractive test of whether investors are able to filter away extraneous news. First, earnings announcements are frequent, quantifiable, and directly value-relevant. Second, several pieces of evidence suggest that limited attention affects stock price reactions to a firm's earnings announcements. The post-earnings announcement drift anomaly (Bernard and Thomas (1989)) suggests that some investors at least temporarily neglect the information in earnings surprises about future profitability. Furthermore, there is evidence that market reactions to earnings announcements are more prompt and complete when there is reason to think investors are paying attention to earnings: during trading hours rather than non-trading hours (Francis, Pagach, and Stephan (1992), Bagnoli, Clement, and Watts (2005)), on non-Friday weekdays rather

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[3]Distracting news may also create information processing bottlenecks for analysts. For example, an internal review committee's job of evaluating analyst reports is harder when there is more information to process.

than on Fridays as the weekend approaches (DellaVigna and Pollet (2006)), and during up markets rather than down markets (Hou, Peng, and Xiong (2006)).

The competing news events that we examine are also earnings surprises. Since all publicly traded U.S. firms need to make earnings announcements, earnings surprises provide an extensive sample of distracting events. Of course, earnings announcements by other firms can be relevant for the value of a given test firm. Indeed, there is literature that tests whether earnings announcements conveys information across firms. However, even if such information transfer exists, each firm's earnings announcement is typically much more informative about its own value than about the value of other firms. Thus, if attention is limited, earnings announcements by other firms can call investor attention away from the purpose of valuing the given firm. Such distraction by extraneous news can potentially weaken the market reaction to its earnings surprise.

Our study adds to a recent literature that provides evidence suggesting that limited attention may affect both market prices and the decisions of investors and financial professionals. Evidence that stock prices underreact to public news events[4], and that information seems to diffuse gradually across industries, between large and small firms, between economically linked firms, and between firms that are followed by different numbers of analysts[5] is consistent with limited attention causing investors to neglect public information (although other possible explanations have also been offered). Evidence that the stock market sometimes reacts to previously-published news[6] suggests that relevant information is neglected at the time of the previous news. Some studies test for the effects of limited attention by examining how investors trade in response to public news arrival.[7]

The past empirical literature on investor attention discussed above has primarily focused on the neglect of public information signals, and on how greater publicity draws

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[4]On the new issues puzzle, see Loughran and Ritter (1995); on the repurchase anomaly, see Ikenberry, Lakonishok, and Vermaelen (1995); on other types of events, see the review of Hirshleifer (2001). Recent papers also test whether investors neglect demographic information (DellaVigna and Pollet (2007)) and information in oil prices (Pollet (2005)). Klibanoff, Lamont, and Wizman (1998) find that in typical weeks closed-end country fund prices underreact to shifts in net asset value (NAV), but underreact much less during weeks in which news about the country appears on the front page of the *New York Times*. They argue that this news is redundant given NAV (which is publicly observable), and therefore suggest that publicity about the country causes the greater reaction in the fund price.

[5]See, e.g., Brennan, Jegadeesh, and Swaminathan (1993), Cohen and Frazzini (2006), Hong, Lim, and Stein (2000), Hong, Torous, and Valkanov (2007), Hou (2007); Hou and Moskowitz (2005) report that delay-prone firms have anomalous returns.

[6]Ho and Michaely (1988); Huberman and Regev (2001) analyze in detail a case of a particular company in which salient reporting of already-public information in the news media about a company led to extreme price reactions.

[7]See, e.g., Barber and Odean (2006), Hirshleifer, Myers, Myers, and Teoh (2003), Linnainmaa (2007), and Seasholes and Wu (2005).

attention to the firm. A distinctive feature of our paper is that it focuses on the competing signals that draw investor attention *away* from a given firm. In other words, our aim is to test *directly* whether extraneous news distracts investors, causing market prices to underreact to relevant news.

For our initial tests of the investor distraction hypothesis, we perform quarterly two-way independent sorts of stocks based on the earnings surprise, and by the number of earnings announcements by other firms on the same day as the firm's earnings announcement. We call days with a large number of competing announcements "high-news days," as opposed to "low-news days." We find that investors' announcement date reactions to earnings news are significantly less sensitive to earnings news on high-news days than on low-news days; the interdecile spread of announcement-period abnormal returns between firms with high and low earnings surprises is 7.07% for low-news days (the bottom number of announcements decile) and 5.67% for high-news days (the top number of announcements decile).

To ensure that our results are not driven by seasonalities or cross-sectional differences in stock price reactions to earnings news, we also perform multivariate regressions that control for the calendar effects (day of week, month, and year) on the sensitivity of market reactions to earnings surprises, as well as the effect of size, book-to-market, the number of analysts following, reporting lags, and institutional ownership. Using multivariate analysis, we find a similar result that the announcement date return response is significantly less sensitive to earnings news when there is a greater number of competing announcements on the same day.[8]

If competing news is distracting, it may also weaken the trading volume response to earnings announcements. Using regression analysis, we find that the abnormal trading volume response to earnings is significantly weakened when the earnings announcement occurs on a high-news day than on a low-news day. Together, these announcement-period volume and return findings are consistent with competing news events drawing investor attention away from a firm's earnings announcements, and thereby weakening the initial price and trading response to these announcements.

To further test the investor distraction hypothesis, we examine whether post-earnings announcement drift is stronger when earnings announcements occur on days with many competing announcements. When we sort stocks based upon the earnings surprise and by the number of earnings announcements on the same day, we find that the post-earnings announcement drift is significantly stronger on high news days. For high-

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[8]In the previous version, we used the residual number of announcements after regressing the number of announcements on day of week, month, and year dummy variables as a measure of distraction and found similar results.

news days, the interdecile spread of the post-announcement 60-day cumulative abnormal returns between high earnings surprise firms and low earnings surprise firms is 7.41% and significant at the 1% level. The spread is only 2.81% and marginally significant at the 10% level for low-news days. Regression analyses also confirm that post-announcement drift is significantly stronger for earnings announcements made on days with a greater number of competing announcements after controlling for other possible determinants of drift.

Taken together, the univariate and multivariate findings that high-news days are associated with a lower sensitivity of announcement abnormal returns to earnings news, with a higher sensitivity of post-announcement abnormal returns to earnings news, and with a lower trading volume response to earnings news, support the investor distraction hypothesis.

When we examine market reactions to positive and negative earnings news separately, we find that the distraction effect is greater in firms receiving positive earnings news. A possible explanation lies in the fact that attention-drawing events including extreme news for a given firm are on average associated with individual investor purchases (Barber and Odean (2006)). After negative news, this amounts to contrarian trading, which tends to mute the market response to the surprise, whereas after positive news, this is positive feedback trading, which tends to strengthen the immediate market response to the surprise.

There may be reasons other than distraction why the number of competing announcements affects the sensitivity of returns to earnings. As discussed in Section 4, it is not entirely obvious why this should be the case. One possible reason is that the number of competing announcements affects the informativeness of a given firm's earnings surprise. However, the distraction hypothesis implies that the number of competing news announcements has opposite effects on the immediate reactivity of the firm's stock to its earnings surprise, versus the post-event reactivity. To compete with the distraction hypothesis, any alternative explanation faces the hurdle of explaining these opposite effects.

Our findings also suggest that an investor who seeks to exploit post-earnings announcement drift can gain by taking into account the amount of competing news on earnings announcement dates. To test whether the number of competing news announcements is useful information for trading strategies, we form portfolios based upon earnings surprises and upon the number of competing events on the day of earnings announcement. At the end of each month, we perform an independent double sort of stocks into $5 \times 5 = 25$ groups based on their most recent quarterly earnings announcements within the preceding three months and the number of announcements on the

announcement day. The portfolio that is long in good earnings news firms and short in bad earnings news firms within the lowest number of announcements quintile is called the "low-news portfolio." Similarly, the long-short earnings portfolio formed from firms with the highest number of announcements is termed the "high-news portfolio."

We find that taking into account extraneous news is useful for portfolio trading strategies. The Fama-French three-factor alphas associated with these portfolios differ significantly across the number of announcements quintiles; the 3-factor alpha is 1.64% per month and highly significant for the high-news portfolio, while it is 0.77% and insignificant for the low-news portfolio.

Different competing announcements may affect attention differently. Investors who follow only a particular sector may find earnings announcements by same-industry firms more distracting than announcements by firms in other industries. On the other hand, the opposite effect is also possible that announcements by same-industry firms help investors react more efficiently to a given announcement. For example, the announcement of record-high earnings by Pixar might attract *more* investor attention to other entertainment firms' earnings announcements on the same day, either because of greater press coverage of the entertainment industry on that day, because the announcement inherently draws investor attention to the entertainment industry, or because a focus on one entertainment firm makes it easier for investors to process information about entertainment industry firms. If such attention-drawing effects occur, the news about Pixar should then distract investors from earnings announcements by firms in different industries.

This suggests that there may be a difference between the effect of industry-related versus industry-unrelated announcements on the attention that investors devote to the earnings announcements of a given firm. To test for such a difference, we separate competing announcements into related and unrelated announcements, using the Fama-French 10 industry classification to measure industry relatedness. We find that a greater number of unrelated announcements reduces the sensitivity of announcement-period returns to earnings news, consistent with the results using the total number of announcements. Furthermore, this distraction effect is stronger for unrelated announcements than related announcements. Similarly, a greater number of unrelated announcements significantly strengthens post-earnings announcement drift; and does so more strongly than does related news.

Overall, our evidence about announcement period returns, post-earnings announcement drift, and trading volume responses are generally consistent with the investor distraction hypothesis. These findings therefore suggest that limited investor attention affects investor behavior and capital market prices.

# 2 Psychological Basis for Distraction Effects

Psychologists have provided a great deal of evidence that it is hard to process multiple information sources or perform multiple tasks at the same time. The interfering effect of extraneous information is illustrated by the famous Stroop task (Stroop (1935)), in which subjects are asked to name the color in which a word is printed, when the word does not match its print color, e.g., the word "blue" printed in red ink. When the meaning of the word differs from its print color, subjects are slower to name its color, as compared, e.g., with naming the color of a geometrical figure.

*Selective attention* involves the focus (conscious or otherwise) on a portion of a scene or set of stimuli. In some studies of selective attention, individuals are asked to direct their attention toward a stimulus, which interferes with the processing of another. In studies of *dichotic listening* (Cherry (1953), Moray (1959), Broadbent (1958)), two messages are separately and simultaneously played into a subject's left and right ear using headphones. In some studies, subjects are asked to attend to one of two messages, and 'shadow' (repeat back) the words of this message. They are then asked questions about the message they were not attending to. Subjects absorb very little information about the unattended message—whether the voice was male or female, but not what language was spoken or any of the words that were spoken, even if the same word is spoken repeatedly

In visual studies of selective attention, participants often think that they have absorbed a scene fully when in fact they have only absorbed the subset of details upon which they have focused. Selective attention leads to 'change blindness' (wherein a noteworthy change in a visual scene is not noticed; see Simons and Levin (1997)). The phenomenon of 'inattentional blindness' involves the failure to perceive task-unrelated stimuli while performing a visual observation task. In such experiments, participants often fail to notice even seemingly conspicuous events in the video scene they are observing—such as a woman walking by in a gorilla suit, stopping, and beating her chest before moving on (Simons and Chabris (1999)).

Studies of *divided attention* and *dual task performance* ask participants to attend to multiple stimuli at the same time and to respond to them. In the auditory domain, a dichotic listening experiment can be used to examine the effects of divided attention. In such an experiment, subjects can be asked to pay attention to *both* messages, and later can be asked about the content of each. Studies of dual task performance have found that there is interference between tasks (see, e.g., Pashler and Johnston (1998)), and that performance is much worse when the two tasks are similar, as with tasks involving the same sensory modalities (McLeod (1977), Treisman and Davies (1973)).

In a financial context, the problem of reacting to multiple earnings surprises by revaluing two different stocks divides attention, and therefore may also be hard to do. Performing valuations involves using similar kinds of information and types of cognitive processing, potentially leading to interference between tasks. Regardless of whether this is the case, more generally, time and cognitive constraints compel restricting attention to a limited set of inputs and tasks.

An investor who tries to forecast firms' prospects are faced with the arrival of many information signals over time. Psychologists have studied experimentally how subjects learn over time to forecast a variable that is stochastically related to multiple cues.[9] A consistent finding in both animal and human studies is that *cue competition* occurs: the arrival of irrelevant cues causes subjects to use relevant cues less. In financial markets, investors presumably try to economize on attention by filtering away irrelevant signals. Nevertheless, psychological evidence of cue competition suggests that stock investors may be more prone to underreact to relevant information about a firm when there is greater arrival of irrelevant signals.

# 3    The Data

We use quarterly earnings announcement data from CRSP-Compustat merged database and IBES from 1995 to 2004. To calculate the daily number of quarterly earnings announcements, we look at quarterly earnings announcements available from CRSP-Compustat merged database. When the announcement date is also available at IBES but is different from Compustat date, we take the earlier date following the imputation rule of DellaVigna and Pollet (2006).[10] While the accuracy of the announcement date is likely to be higher when it is available from both IBES and Compustat, we include Compustat earnings announcements without matching IBES data when we compute the number of competing announcements each day because IBES coverage is for relatively large firms.[11] Our sample firms are limited to those that have IBES coverage; we therefore expect very accurate announcement dates for our sample even though the number of competing announcements can be slightly noisy.

To estimate the forecast error (FE) as a measure of the earnings surprise, we calculate the difference between announced earnings as reported by IBES ($e_{iq}$) and the consensus earnings forecast ($F_{iq}$), defined as the median of the most recent forecasts

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[9]See, e.g., Baker, Mercier, Valleettourangeau, Frank, and Pan (1993), Busemeyer, Myung, and McDaniel (1993), and Kruschke and Johansen (1999).

[10]DellaVigna and Pollet (2006) report that the accuracy of announcement dates imputed from IBES and Compustat are almost perfect in the post-1994 period.

[11]According to Hong, Lim, and Stein (2000), 40% of CRSP firms are not covered by IBES in 1994.

from individual analysts. To exclude stale forecasts when we calculate the consensus forecast, we only include 1- or 2-quarter ahead forecasts issued or reviewed in the last 60 calendar days before the earnings announcement. If an analyst made multiple forecasts during that period, we take her most recent forecast. The difference between the announced earnings and the consensus forecast is normalized by the stock price at the end of the corresponding quarter ($P_{iq}$), where earnings, forecasts, and stock prices are all split-adjusted. To control for possible data errors, we delete observations when earnings or forecasts are greater than the stock price, or when the stock price is less than \$1 before split-adjustment.

$$FE_{iq} = \frac{e_{iq} - F_{iq}}{P_{iq}}. \tag{1}$$

The cumulative abnormal returns of the announcement window and the post-announcement window are defined as the difference between the buy-and-hold return of the announcing firm and that of a size and book-to-market (B/M) matching portfolio over the windows $[0, 1]$ and $[2, 61]$ in trading days relative to the announcement date,

$$
\begin{aligned}
CAR[0, 1]_{iq} &= \prod_{k=t}^{t+1}(1 + R_{ik}) - \prod_{k=t}^{t+1}(1 + R_{pk}) \\
CAR[2, 61]_{iq} &= \prod_{k=t+2}^{t+61}(1 + R_{ik}) - \prod_{k=t+2}^{t+61}(1 + R_{pk}),
\end{aligned}
\tag{2}
$$

where $R_{ik}$ is the return of the firm $i$ and $R_{pk}$ is the return of the matching size-B/M portfolio on day $k$ where $t$ is the announcement date of quarter $q$'s earnings.

We choose 60 trading days for the post-announcement window because Bernard and Thomas (1989) report that most of the drift occurs during the first 60 trading days after the announcement (about three calendar months). Each stock is matched with one of 25 size - B/M portfolios at the end of June based on the market capitalization at the end of June and B/M, the book equity of the last fiscal year end in the prior calendar year divided by the market value of equity at the end of December of the prior year. The daily returns of 25 size - B/M portfolios are from Kenneth French's website.[12]

# 4 The Effect of Competing News on Announcement Date Returns, Volume, and Post-Earnings Announcement Drift

We specify the investor distraction hypothesis as containing three parts:

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[12]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

**Hypothesis 1a:** The sensitivity of the announcement abnormal return to earnings news decreases with the number of competing announcements.

**Hypothesis 1b:** The abnormal trading volume on the day of announcement decreases with the number of competing announcements.

**Hypothesis 1c:** The sensitivity of the post-announcement abnormal return to earnings news increases with the number of competing announcements.

Hypotheses 1a and 1c predict opposite directions for the effect of the number of competing news announcements on the announcement-period sensitivity of the firm's stock return to its earnings surprise, versus the sensitivity of the post-event return. This helps distinguish the investor distraction hypothesis from alternative theories. For example, it might be argued that competing news announcements affect the informativeness of the firm's earnings announcement. However, such an alternative theory predicts the same direction of effect on the announcement period and the post-event sensitivity of returns to the firm's earnings surprise (holding constant the fraction of the total response to the earnings surprise that is delayed).

## 4.1   Descriptive Statistics

Table 1 reports the descriptive statistics of daily number of quarterly earnings announcements. The mean number of announcements a day is 120.8 and the median number is 71. The percentiles of the number of announcements show that there is a wide variation in the number of earnings announcements per day; the 10th percentile number of announcements is 20 and the 90th percentile is 290. Earnings announcements seem to cluster by day of week and show a highly seasonal pattern. As documented by other studies, the number of announcements is higher on Tuesday, Wednesday, and Thursday, and lowest on Friday (e.g., Damodaran (1989), DellaVigna and Pollet (2006)); the average number of announcements on Friday is 68.8, which is less than a half of the average number of announcements on Thursday (152.2).

When examined by month, the number of announcements shows an approximately 3-month cycle, with the lowest number of announcements in March, June, September, and December. This pattern reflects the fact that about 60% of the announcements are for fiscal quarters ending in March, June, September, and December and that it takes one to two months from the end of fiscal quarter until the earnings announcement date.[13]

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[13]In 2002, SEC deadline for filing quarterly reports was 45 days of quarter end and 90 days of year end for annual reports. The deadlines are now accelerated to 35 days for quarterly reports and 60 days for annual reports for fiscal years ending on or after December 15, 2005.

Table 2 shows the average size and book-to-market ratios by the decile rank of the number of announcements. The decile rank is based on quarterly sorts of earnings announcement observations by the number of announcements on the announcement day. Earnings announcements on high-news days are from larger firms than those on low-news days ($p < 0.001$), while there is no significant difference in book-to-market ratios between the two extreme number of announcements deciles. However, the size and book-to-market ratios are not monotonic across the number of announcement deciles. Deciles 3 and 4 have relatively low size and high book-to-market ratios.

## 4.2 Announcement Date Returns and Post-Earnings Announcement Drift

We first perform univariate analysis to examine the effect of competing news on price reactions to earnings news. In each calendar quarter, we perform a two-way independent sort of all quarterly earnings announcements observations in that quarter into $10 \times 10 = 100$ groups based upon the number of earnings announcements on the day of the earnings announcement and the earnings surprise (forecast error) as defined in Equation (1). We exclude earnings announcements for which we lack the size or book-to-market information of the announcing firm needed to calculate abnormal returns. For each number of announcements decile, we calculate the mean announcement-period and post-announcement cumulative abnormal returns for the most positive (FE10) and the most negative earnings surprise deciles (FE1), and the difference of announcement and post-announcement cumulative abnormal returns between the two extreme earnings surprise deciles.

The spread of announcement-day abnormal returns between earnings surprise deciles 10 and 1 (FE10 − FE1) measures the stock price response to earnings news; a larger spread indicates that investors react more strongly to earnings news on the announcement date. The spread of *post-announcement* abnormal returns between earnings surprise deciles 10 and 1 measures underreaction to earnings news as reflected in subsequent drift. If the market is efficient, there will be no difference between good-earnings-news and bad-earnings-news firms in their post-announcement abnormal returns. A positive spread indicates underreaction to earnings news – positive abnormal returns following good news and negative abnormal returns following bad news.

Table 3 shows that investors' 2-day announcement reactions to earnings news are less sensitive to earnings news when earnings are announced on high-news days (NRANK=10) than low-news days (NRANK=1). For the lowest number of announcements decile (low-news days), the mean spread in 2-day cumulative announcement returns (CAR[0,1])

between good earnings news firms (FE10) and bad earnings news firms (FE1) is 7.07%, whereas for the highest number of announcements decile, the mean spread is 5.67%. This indicates that the price reactions to earnings news are stronger when earnings are announced on low-news days than on high-news days.

Greater competing news is also associated with stronger post-earnings announcement drift. The spread in mean 60-day post announcement abnormal returns (CAR[2,61]) between good and bad earnings news deciles indicates greater underreaction to earnings news on high-news days than on low-news days. For high-news days, the post-announcement abnormal return spread between extreme earnings surprise deciles is substantial (7.41%) and highly significant ($p < 0.001$), whereas the low-news days spread is smaller (2.81%) and marginally significant($p = 0.055$). However, the spread in the post announcement abnormal returns is not monotonic across the number of announcements deciles (NRANK). The source of this non-monotonicity may be differences in size and

B/M across the number of announcement deciles (see Table 2). Therefore, we conduct multivariate regression analysis in Subsection 5.1 to control for the effect of firm characteristics such as size, book-to-market, and calendar effects (day of week, month, or year) on the relation between announcement or post-announcement abnormal returns and earnings news.

To examine the interaction effect of earnings surprise and the amount of competing news, we use an ANOVA procedure to test if the abnormal returns spread between high and low earnings surprise deciles is significantly different between low and high news days. This is equivalent to testing the significance of the interaction term $a_3$ in the following regression, using all announcements in the top and bottom of the earnings surprise deciles and top and bottom of the number of announcements deciles:

$$CAR = a_0 + a_1(FE10) + a_2(NRANK10) + a_3(FE10)(NRANK10) + \varepsilon, \qquad (3)$$

where $FE10$ is an indicator variable that is equal to 1 for the top decile of earnings surprise, $NRANK10$ is an indicator variable that is equal to 1 for the top decile of the number of announcements (high-news days), $CAR = CAR[0,1]$ for the announcement date abnormal returns, and $CAR = CAR[2,61]$ for the post-announcement cumulative abnormal return. Thus, the ANOVA procedure tests whether $CAR$ spreads between good and bad earnings news firms are different between high and low news days.

The ANOVA procedure confirms that a greater number of competing announcements mutes the announcement-date stock price reaction to a firm's earnings surprise. The last row of Table 3 reports the difference between high and low news days. The difference between high and low news days in interdecile spreads of $CAR[0,1]$ is $-1.40\%$ and statistically significant ($p = 0.033$). The difference of interdecile spreads of $CAR[2,61]$

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is 4.60%, and also statistically significant ($p = 0.034$).

Figures 1 and 2 provide graphical evidence that market reactions to earnings news is weaker on the announcement day and subsequent drifts are stronger when earnings are announced on high-news days than low-news days. In Figure 1, the abnormal announcement return (CAR[0,1]) is plotted against earnings surprise deciles, separately for high-news days (Decile 10) and for low-news days (Decile 1). The market reaction is less sensitive to earnings news on high-news days, as reflected by its flatter slope in the graph. Furthermore, it appears that the difference in the sensitivity between high and low news days is more pronounced among positive rather than negative earnings surprises. We examine the distraction effect separately for positive and negative earnings surprises later in Subsection 5.1.

Figure 2 shows the mean post-announcement abnormal returns (CAR[2,61]) as a function of earnings surprise deciles. The slopes of the graphs show that post-announcement abnormal returns are more predictable based on earnings news when earnings are announced on high-news days than low-news days, consistent with a more sluggish reaction to earnings news announced on high-news days. Figures 1 and 2 and the univariate results in Table 3 suggest that investors react more sluggishly to earnings news when they are distracted by competing announcements.

# 5    Regression Analysis

To control for other possible determinants of investor responses to earnings news, we perform multivariate tests. Subsection 5.1 describes how competing news affects the sensitivity of returns to a firm's earnings news. Subsection 5.2 describes how competing news affects the sensitivity of trading volume to a firm's earnings news.

## 5.1    Distraction and the Return Response to Earnings News

In Subsubsection 5.1.1 we describe full sample tests. We perform additional analysis and consider alternative explanations in Subsubsection 5.1.2. Then in Subsubsection 5.1.3 we provide tests in subsamples of positive versus negative earnings surprises.

### 5.1.1    Full Sample Tests

In order to control for possible sources of variation in the relation between announcement date returns and earnings news and also between post-announcement drifts and earnings news, we run regressions of two-day announcement abnormal return (CAR[0,1]) or 60-day post-announcement abnormal return (CAR[2,61]) on the earnings surprise decile

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rank (FE), the number of announcements decile rank (NRANK), the interaction term (FE×NRANK), control variables, also interacted with FE,

$$CAR = a_0 + a_1 FE + a_2 NRANK + a_3 (FE \times NRANK) + \sum_{i=1}^{n} c_i X_i + \sum_{i=1}^{n} b_i (FE \times X_i) + \varepsilon. \quad (4)$$

The investor distraction hypothesis posits that announcement return is less sensitive and post-announcement return is more sensitive to earnings news on high news days. Thus, we expect $a_3 < 0$ when we use CAR[0,1] as dependent variable and $a_3 > 0$ when we use CAR[2,61] as dependent variable.

Following past literature, we use the decile rank of forecast error as opposed to the forecast error itself. This reduces the influence of outliers, and linearizes the relation between abnormal returns and the earnings surprise (see Figure 1). Previous research shows that investor reactions to earnings news vary with firm size, book-to-market ratios, number of analysts following, reporting lags, institutional ownership, and day of the week.[14] Thus, we include as control variables size and B/M deciles, the number of analysts following the firm during the most recent fiscal year (Log(1+# analysts following)), reporting lags (the number of days from the quarter end until the announcement date), institutional ownership, and day of week/month/year dummies. Institutional ownership (IO) is the percentage of shares owned by institutions at the end of the most recent calendar quarter constructed from the CDA/Spectrum 13F database. Standard errors of regression coefficient estimates are adjusted for heteroskedasticity and clustering by the day of announcement.

The regression results in Table 4 describe the sensitivity of the immediate stock price reaction (CAR[0,1]) and the delayed response (CAR[2,61]) to the earnings surprise as a function of the amount of competing news. The coefficient on the interaction between earnings surprise rank and the number of competing announcements rank (FE×NRANK) measures the effect of competing announcements on market reactions to earnings news. For the announcement return (CAR[0,1]), the coefficient of the interaction term (FE×NRANK) is negative ($-0.021$) and significant at the 1% level (Regression 1). Since the coefficient estimate for FE is 1.027, this implies that the market reactions are about 20% less sensitive to earnings news on high-news days (NRANK=10) compared to those on low-news days (NRANK=1).[15]

For post-announcement abnormal returns (CAR[2,61]), the coefficient on the interaction between earnings surprise decile rank and the number of announcements rank (FE×NRANK) is positive (0.049) and significant at the 1% level after controlling for

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[14]E.g., Bernard and Thomas (1989), Chambers and Penman (1984), DellaVigna and Pollet (2006).

[15]The sensitivity is $1.027 - (0.021 \times 10) = 0.817$ for NRANK=10 and $1.027 - (0.021 \times 1) = 1.006$ for NRANK=1.

the effect of size, B/M, analyst following, reporting lags, institutional ownership, and day of week, month, and year (Regression 5).

Thus, consistent with the distraction hypothesis, distracting news has opposite effects on the sensitivity of a firm's announcement period returns to its earnings surprise versus the sensitivity of its post-announcement reaction to its earnings surprise. These opposite effects raise a challenging hurdle to alternatives explanations such as one based upon the informativeness of earnings announcements.

We also examine whether the distraction effect varies with firm size, analyst following, or institutional ownership. The distraction effect is measured by the coefficient estimate of FE×NRANK, which is negative in the announcement-return regression (weaker response for high-news day announcements) and positive in the post-announcement regression (stronger drift after high-news day announcements). To test whether firm size, analyst following, or institutional ownership affects the distraction effect, we include a triple interaction term (FE×NRANK×$X_i$, where $X_i$=SIZE, Log(1+#Analysts), or IO) in Regressions (2)-(4) and (6)-(8). There is weak evidence that the distraction effect is stronger among firms with small market capitalizations, low analyst following, or low institutional ownership. For example, FE×NRANK×SIZE is positive and significant at 10% in Regression (2), implying that the distraction effect on announcement returns (negative FE×NRANK) is muted among larger firms. For the post-announcement drift, FE×NRANK×SIZE is negative and significant at 10% in Regression (6), implying that the distraction effect on post-announcement returns (positive FE×NRANK) weaker among larger firms.

### 5.1.2   Additional Analysis and Alternative Explanations

We consider several alternative explanations of our findings. First is the presence of errors in announcement dates. The sensitivity of the announcement-day abnormal return to earnings news can be weaker and the sensitivity of the post-announcement abnormal return to earnings news stronger on high-news days if there are more errors in our announcement dates in the top number of announcement decile (high-news days). If the actual announcement date is later than our announcement date, our post-announcement period [2,61] may include the actual announcement date. A higher incidence of such errors among high news days could contribute to the weaker/stronger relation between announcement/post-announcement abnormal returns and earnings surprises on high-news days.

We check the accuracy of our announcement dates with the news-wire announcement dates of DellaVigna and Pollet (2006).[16] DellaVigna and Pollet (2006) hand-collected

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2,766 randomly-selected earnings announcements from 1984 to 2003 using Lexis-Nexis and the PR news-wires. We are able to match 159 out of 11,764 low-news day announcements (NRANK=1) with the news-wire announcement dates. Out of 159 announcements, 3 announcements are different from the news wire announcement dates; two of our announcement dates are earlier than the news wire dates by 1 day, one is earlier than the news wire date by 3 or more days. For high-news day announcements (NRANK=10), 59 out of 12,185 announcements are matched with the news-wire announcement dates and 3 of the matched announcements are different from the news-wire dates; for all three, our dates are earlier than the news wire dates by one day. The error rate is indeed greater in the high news days than low news days. However, the sample is too small for the difference in error rates to be statistically significant.

To address the possible effect of errors in announcement dates on return sensitivities, we compute announcement and post-announcement abnormal returns using different windows. The dependent variable in Regression 1 in Table 5 is the abnormal return over days [−1,1] of the announcement. Including day −1 can help in case the actual announcement as reported in news wires is earlier than our announcement date imputed from Compustat and IBES.[17] When the actual announcement is later than our announcement date, our post-announcement window may capture the actual announcement date and therefore we could find stronger predictability of post-announcement abnormal returns based on earnings news.[18] To address this possibility, in Regression 2 in Table 5, we start the post-announcement window from day 3. We find that the results are quite similar when we use different windows for computing announcement and post-announcement abnormal returns. We therefore conclude that errors in announcement dates are not likely to affect the results.

Second, it is possible that high-news days are associated with weaker reactions on the announcement date because there is more leakage of earnings news before the announcement. To address this possibility, in Regression 3 we examine 30-day abnormal returns before the announcement. We find that in this pre-announcement period, the relation between announcement abnormal returns and earnings news does not differ significantly across NRANK. Thus, there is no indication of any difference in information leakage in relation to NRANK.

One may argue that the number of distracting events affects the informativeness of the firm's earnings about fundamental value. We do not see any clear reason why

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Joshua Pollet for providing the data.

[17]However, we did not find any such cases among our announcement dates matched with the news-wire dates from DellaVigna and Pollet (2006).

[18]However, none of the actual (news-wire) announcement date falls in the post-announcement window [2,61] for high-news day announcements in our matched announcement dates sample.

the number of competing announcements should affect the informativeness of the given firm's earnings surprise or the sensitivity of its stock price to its own earnings surprise, or any presumption as to which way such an effect would go. However, if a given firm's earnings were more informative at times when there are few competing announcements, we would expect both the immediate and total price response to the firm's earnings announcement to be larger at such times. To evaluate this alternative hypothesis, we test directly whether low-news days are associated with a stronger total sensitivity of stock prices to earnings news. Regression 4 shows that the sensitivity of abnormal returns over days [0,61] to earnings news, which measures the total impact of earnings news on stock prices, does not differ across the number of announcement deciles.

Another alternative interpretation of our findings is that in the short run the amount of capital available to sophisticated investors to arbitrage post-earnings announcement drift is limited. Since in practice even short-selling requires capital, when NRANK is high there are many competing uses for arbitrage capital (to exploit the large number of earnings surprises). So even if there is no limited attention, high NRANK could imply a lower immediate reaction to a given earnings surprise, and therefore stronger post-announcement drift.

However, the arbitrage capital argument is actually ambiguous, because earnings announcements can free up, rather than take up, arbitrage capital. If arbitrageurs have already taken a position in a stock for any reason, then when it announces earnings and uncertainty is resolve, arbitrageurs have an opportunity to reverse out their positions.

Furthermore, even if it be the case that arbitrageurs are on the whole committing more rather than less capital in response to earnings surprises, the capital constraints argument has a counterfactual implication. Professional arbitrageurs are most active in large and more liquid stocks. This suggests that small naive investors would be more important for the price-setting of small stocks, and sophisticated professional arbitrageurs would have the greatest influence on the prices of large and liquid stocks. If so, then shocks to the scarcity of arbitrage capital will have a bigger effect on arbitrage activity in larger stocks. Thus, the arbitrage capital argument implies that the distraction effect should be greatest among larger stocks. However, our evidence in Table 4 indicates if anything the opposite–the distraction effect seems stronger among small stocks.

### 5.1.3 Positive versus Negative Earnings Surprises

Past research has shown that stock returns are more sensitive to the size of positive earnings surprises than the size of negative ones (Hayn (1995)). Since these reactions are asymmetric, it is interesting to examine separately the effect of competing announcements for positive and negative earnings surprises.

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Table 6 reports regression evidence for the positive and negative earnings surprise subsamples. $NRANK$ is the decile rank of the number of announcements as defined earlier and $FE$ is the quintile rank of the earnings surprise within each subsample of positive or negative earnings surprises.

The effect of competing news on market reactions to earnings news is very different in the two samples. As with the full sample, for positive earnings news, the number of announcements significantly reduces the sensitivity of announcement abnormal return to positive earnings news. Similarly, the number of announcements significantly increases the sensitivity of post-announcement abnormal return to positive earnings news. For the announcement return regression, the coefficient of the interaction term $FE \times NRANK$ is $-0.039$ and significant at the 1% level, and in the post-announcement return regression is $0.120$ and significant at the 5% level.

In contrast, in the negative earnings news subsample, the effect of competing news on the market reactions to news is insignificant for the immediate reaction, though it is positive (0.156) and significant for long-term drift. While the coefficient of the interaction term $FE \times NRANK$ is greater for the negative surprise sample (0.156 versus 0.120), it seems that the significance of the term $FE \times NRANK$ for the negative surprise sample is driven not by underreaction, but by the relation between NRANK and the sensitivity of the *total* price reaction to earnings news (in the regression with CAR[0,61] as dependent variable, $FE \times NRANK$ is significant at the 5% level for the negative surprise sample and insignificant for the positive surprise sample). Therefore, the results suggest that distraction has a greater effect on underreaction to positive than to negative earnings.

A possible explanation lies in the fact that attention-drawing events, including extreme news, are on average associated with individual investor purchases (Barber and Odean (2006)). Barber and Odean suggest that this results from the combination of limited attention, and the asymmetry between stock buying and selling. An investor selects stocks to purchase from a potential universe of thousands of stocks, but sells are mostly limited to the few stocks in the investor's portfolio. Thus, extreme news about a stock, whether good or bad, brings investor attention to that stock, and on average leads to a greater preponderance of buying over selling.[19]

This suggests that attention-driven purchases after bad news may weaken market reactions to this news. To the extent that distraction mutes attention-driven contrarian trading after negative news, distraction can strengthen instead of weaken the immediate response to the negative surprise. This effect can potentially offset the basic distraction

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[19]Although their proxies for investor attention do not include distracting information, Hou, Peng, and Xiong (2006) also provide evidence suggesting that attention has a larger effect on market reactions to positive than to negative earnings news, and refer to the asymmetry between buying and selling decisions.

effect that motivates our tests.

The reasoning is different after good news, which, as shown by Barber and Odean, is also associated with attention-driven buys. Such buying should tend to magnify the price reaction to the positive news. To the extent that distraction mutes this attention-driven buying after positive news, distraction will tend to weaken the immediate response to the positive surprise. Thus, this effect potentially reinforces the basic distraction effect that motivates our tests.

In summary, when we take into account that the effect of distraction is likely to be different for investor buys and sells, there are possible offsetting effects on how distraction affects price reactions to bad news; but the prediction remains unambiguous for the effect of distraction on price reactions to good news.

## 5.2 Distraction and the Volume Response to Earnings News

The extent to which investors react to earnings news can also be measured by trading volume in response to the earnings announcement. The investor distraction hypothesis holds that competing announcements will mute the trading volume response to earnings news.

We define abnormal volume on day $j$ relative to the announcement date $t$ as a normalized difference between the log dollar volume on day $j$ and the average log dollar volume over days $[-41, -11]$ of the announcement:

$$VOL[j] = Log\left(DollarVol_{t+j} + 1\right) - \frac{1}{30} \sum_{k=t-41}^{t-11} Log(DollarVol_k + 1). \qquad (5)$$

We perform regression analysis of the abnormal trading volume on the announcement day (VOL[0]) and also two days around announcement (VOL[0,1]). The two-day abnormal trading volume is defined as the average of abnormal trading volumes on the announcement date (VOL[0]) and on the following day (VOL[1]).

Since both extreme positive and negative earnings surprises are likely to generate large trading volume, we regress the one- or two-day abnormal trading volume on the decile rank of *absolute* earnings surprises (AFE), the number of announcement decile rank (NRANK), and other control variables. In addition to the size, B/M, number of analysts following, reporting lags, institutional ownership, and year/month/day of week dummies we employed in the previous section, we also include market abnormal trading volume during the same period (MKTVOL for one-day, MKTVOL2 for two-day window) so that we are not capturing the market-wide variations in trading volumes. MKTVOL

is the average abnormal volume of all CRSP firms on that day where the abnormal volume of each firm is defined in a manner similar to (5).

Table 7 shows that the coefficient of NRANK is negative and significant at the 1% level in all regression models, indicating that both 1- and 2-day abnormal volume is lower when earnings are announced on high-news days compared to low-news days, after controlling for the effect of earnings news or size of earnings news, and market trading volume, firm-characteristics, and calendar effects. To control for a possible non-linear effect of earnings surprise on trading volume, we also use indicator variables for each earnings surprise decile instead of the absolute earnings surprise decile rank (Regressions 3 and 6) and find similar results. Overall, the results show that investor reaction to earnings news as measured by abnormal trading volume is weaker when earnings are announced on high-news days.

# 6    Portfolio Trading Strategies

We now test whether investors can use the distraction effect to form better portfolios. Based on the previous results, we expect investors to be able to achieve superior returns by combining earnings surprise information with information about distracting news, as measured by the number of competing earnings announcements.

At the end of each month from March 1995 until December 2004, we independently sort stocks into 5×5 portfolios based on their most recent earnings surprises within the last three months and the number earnings announcements on the day of earnings announcement. We then calculate equally-weighted returns of each of the resulting 5×5 portfolios during the following month. Within each number of announcements quintile (NRANK), we form a hedge portfolio that is long in the good news portfolio (FE = 5) and short in the bad news portfolio (FE = 1) and compute the return of the hedge portfolio.

If investors underreact to earnings news, the good news portfolio will outperform the bad news portfolio. Therefore, the abnormal return of the hedge portfolio will be larger when there is stronger post-earnings announcement drift. Since quarterly earnings announcements during the preceding three months are used to form portfolios, the strategy uses most of CRSP stocks with quarterly earnings information and captures up to three months of post-announcement returns. We measure monthly abnormal performance of the portfolio using alphas from a time-series regression of the portfolio return (less the risk-free rate except for the zero-cost hedge portfolios) on Fama-French three factors.

Table 8 shows that a trading strategy designed to exploit post-earnings announce-

ment drift achieves a higher abnormal return when implemented on earnings announcements that occur on high-news days than on low-news days. The Good minus Bad earnings news hedge portfolio 3-factor alpha is 1.64% per month and significant at the 1% level for the high-news portfolio (NRANK=5). The alpha is only 0.77% and insignificant for the low-news portfolio (NRANK=1). In other words, there is no discernible post-earnings announcement drift when there is little competing news that distracts investors from the earnings news. The hedge portfolio returns across NRANK are not monotonic, possibly due to small firm sizes in the second number of announcement quintile (deciles 3 and 4 in Table 2).

The "fund-of-fund" portfolio, which is formed by going long in the high-news hedge portfolio and short the low-news hedge portfolio, has a 3-factor alpha of 0.86% which is significant at the 10% level. This indicates that the post-announcement drift portfolio strategy using high-news day announcements earns marginally higher returns than that using low-news day announcements. Also the evidence suggests that the higher profitability of high-news portfolio is mainly due to greater distraction effect on positive news. The 3-factor alpha of the high-minus-low portfolio (NRANK5-NRANK1; last row of Table 8) which is long in high-news portfolio and short in low-news portfolio is 0.48% (significant at 10% level) for the top earnings surprise quintile (FE=5) while it is −0.38% and insignificant for the bottom earnings surprise quintile (FE=1).

The portfolio strategy findings confirm the univariate and regression results that post earnings announcement drift is stronger for earnings announcements made on high-news days than low-news days. The portfolio findings also indicate that, in the absence of transactions costs, the amount of distraction on the day of the earnings announcement is useful information for an investor who seeks to exploit post-earnings announcement drift to achieve superior returns.

# 7  Related versus Unrelated Announcements

So far we have treated all announcements by other firms alike. However, it is possible that not all competing announcements are distracting. If two firms are closely related, an announcement by a one firm might *attract* attention to the other. For example, Google's announcement of its earnings may attract investors' attention to earnings announcements by other internet portal firms, and distract investor attention from the earnings announcements of totally unrelated firms. On the other hand, announcements by related firms can be more distracting to investors who specialize in a particular sector. Therefore, it will be interesting to examine how related and unrelated announcements affect market reactions to earnings news differently.

We identify firm relatedness by whether they are in the same industry using the Fama-French 10 industry classification. The number of related announcements is the number of earnings announcements by same-industry firms; the number of unrelated announcements is the number of announcements by firms in other industries. Since Industry 10 in the Fama-French classification is defined as 'others' which do not belong to any of the pre-defined categories, we limit the analysis to Industries 1-9.

In the regression analyses, we interact the earnings surprise decile rank (FE) deciles with the number of related announcements decile (NrelRank) or the number of unrelated announcements decile (NunrelRank) to test the effect of related and unrelated announcements on investor reactions to earnings news. To address the possibility that some industries on average may have a larger number of related or unrelated announcements, the number of related/unrelated announcements deciles (NrelRank/NunrelRank) are based on quarterly sorts by the number of related/unrelated announcements within each industry.[20]

Table 9 shows that unrelated news distracts investors more strongly than related news. The number of related or unrelated announcements lowers the sensitivity of announcement returns to earnings news when we examine them separately; the coefficient of the interaction term of earnings surprise and the number of related announcement deciles (FE×NrelRank) is −0.015 and significant at the 1% level in Regression 1, and the coefficient of the interaction term of earnings surprise and the number of unrelated announcement deciles (FE×NunrelRank) is −0.021 and significant at the 1% level in Regression 2. When we include both variables, the effect of unrelated news dominates that of related news; FE×NunrelRank is negative significant at the 5% level and FE×NrelRank is insignificant in Regression 3.

We also examine the effect of related and unrelated announcements on post-earnings announcement drift. We find complementary results; the number of unrelated announcements increases the sensitivity of post-announcement returns to earnings news whether or not related announcements are included, but the effect of related news is not significant. The coefficient estimates for the interaction term FE×NunrelRank are positive and significant at the 5% level in Regressions 5 and 6, while the coefficient estimates for the interaction term FE×NrelRank are insignificant in Regressions 4 and 6. In summary, Table 9 provides evidence that it is primarily unrelated news firms that mutes the initial market reaction to earnings news, and thereby intensifies post-earnings announcement drift.

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[20]The results are similar when we form the number of related/unrelated announcements deciles using all sample firms and control for possible industry effects by including industry dummies.

# 8 Why Distraction Can Affect Security Prices

A limited attention explanation for an asset pricing pattern must explain why investors who are not paying full attention would participate in markets and affect prices, and why any such effects are not eliminated by the trades of fully rational arbitrageurs. The issue of arbitrage has been addressed by many papers in behavioral finance; if the risk-bearing capacity of fully rational individuals is finite, then their beliefs do not dominate prices in the short run; instead, prices reflect a weighted average of investor beliefs, where the weights depend on the frequencies of different investor types in the population and on their risk tolerance.[21]

In the long run, we might expect wealth on average to flow from less rational traders to more rational traders, which could diminish the influence of imperfectly rational traders on prices. Again, this is a standard issue in the behavioral finance literature, and there are some standard responses: that stock prices are noisy so that this wealth-transfer process can be slow, that in the long run new generations of naive traders enter the market, and that owing either to aging or to psychological biases in learning processes some investors may learn to be less rather than more rational over time.

In the specific context of limited attention, owing to cognitive resource constraints, *all* investors have limited attention, so there is no way for a flow of wealth to fully eliminate its effects (see, e.g., Hirshleifer and Teoh (2005)). Even if some investors allocate resources heavily to the study of a given stock at a given time, and therefore are highly attentive toward that stock, this entails withdrawal of cognitive resources from other activities, so we cannot conclude that wealth will tend to flow toward such an investor.

A different argument set of arguments against limited attention affecting security pricing are based on investors being able to adjust intelligently to deal with limited attention. For example, one can leverage attention by focusing on more important signals. However, it can be hard to know how important an item is until it is carefully processed.

Alternatively, an investor who is neglecting relevant public information about a stock could withdraw from trading in that stock, so that his beliefs are not reflected in its price. However, the same processing and memory constraints that cause neglect of a signal also make it hard to compensate optimally for the failure to attend to it. For example, an investor whose valuation disagrees with the market price may inattentively fail to reason through why the market price differs from his own valuation. Experimental evidence that the presentation format of decision problems affects choice (e.g., Tversky

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[21]In the context of reactions to earnings news, see the model of Hirshleifer and Teoh (2005).

and Kahneman (1981)) indicates that individuals do not compensate optimally for the limitations in their information processing. Empirically, there are strong indications that investors are very willing to trade even when they do not possess superior valuations (Barber and Odean (2000)).[22]

Other psychological evidence also indicates that individuals do not fully compensate for the fact that they do not possess all relevant information. For example, when presented with one-sided arguments and evidence and asked to judge a legal dispute, experimental subjects were biased in favor of the side they heard (Brenner, Koehler, and Tversky (1996)). As the authors state, "The results indicate that people do not compensate sufficiently for missing information even when it is painfully obvious that the information available to them is incomplete."

Furthermore, we argue that it is reasonable to trade even though one is neglecting some information. Traditional models of information and securities markets such as Grossman and Stiglitz (1976) provide the insight that, owing to liquidity or noise trading, prices aggregate information imperfectly. In consequence, these models imply that even an uninformed individual who is trading against others who are better informed should trade based upon his beliefs rather than lapsing into passivity. Intuitively, such an investor benefits by supplying liquidity to the market, and taking advantage of any mispricing created by liquidity trades. Analogously, even an investor who neglects a public signal can benefit from contrarian trading (e.g., through limit orders) based upon his beliefs. Such contrarian trading could on average be profitable[23], yet could also induce price underreaction to public news events such as earnings announcements.

# 9    Concluding Remarks

This paper contributes to a growing literature indicating that limited investor attention has important effects. A distinctive aspect of our tests is a specific focus on the extraneous news that is the presumptive *source* of possible investor neglect of relevant news. We propose the *investor distraction hypothesis*, which holds that the arrival of extraneous earnings news causes trading volume and market prices to react sluggishly to relevant news about a firm. Specifically, we test the investor distraction hypothesis

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[22]An additional possible source of such neglect is overconfidence, a well-documented psychological bias. An overconfident individual who wrongly thinks that he has already incorporated the most the important signals may not perceive the urgency of adjusting for the fact that he is neglecting a relevant public signal.

[23]Kaniel, Saar, and Titman (2004) find that contrarian trading allows U.S. individual investors to earn positive excess returns in the month after their trades; Linnainmaa (2003) finds that individual day traders in Finland provide liquidity to the market through limit orders and on average profit during the day by doing so.

by examining how the number of earnings announcements by other firms affects the sensitivity of a firm's volume, announcement-period return, and post-event return reaction to its earnings surprise.

Our evidence indicates that the presence of a large number of competing earnings announcements by other firms is associated with a weaker announcement-date price reaction to a firm's own earnings surprise, a lower volume reaction, and stronger subsequent post-earnings announcement drift. A portfolio trading strategy that exploits post-earnings announcement drift achieves superior performance when implemented on earnings announcements on days with a large number of competing announcements than those on days with little competing news. Competing announcements made by firms in other industries have a stronger distraction effect, whereas those by same-industry firms do not have a significant effect.

These findings generally support the investor distraction hypothesis. Furthermore, they indirectly suggest that investors' limited attention may drive the basic anomaly, post-earnings announcement drift. More broadly, this evidence raises the possibility that limited attention is the source of the general pattern documented in several studies of underreaction to a variety of public corporate news events.

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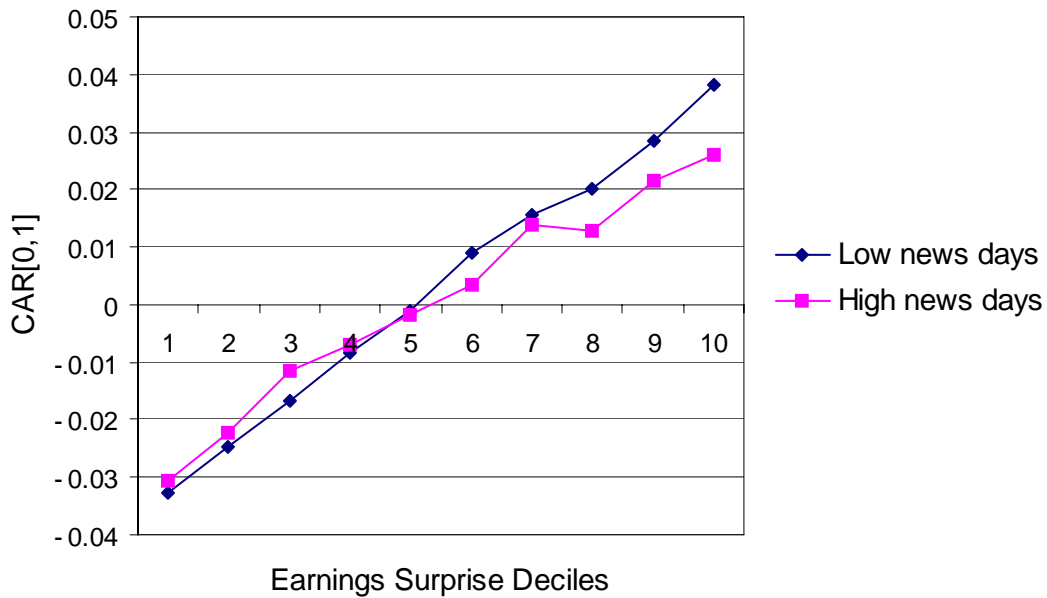
**Figure 1. Market Reactions to Earnings News: CAR[0,1]**
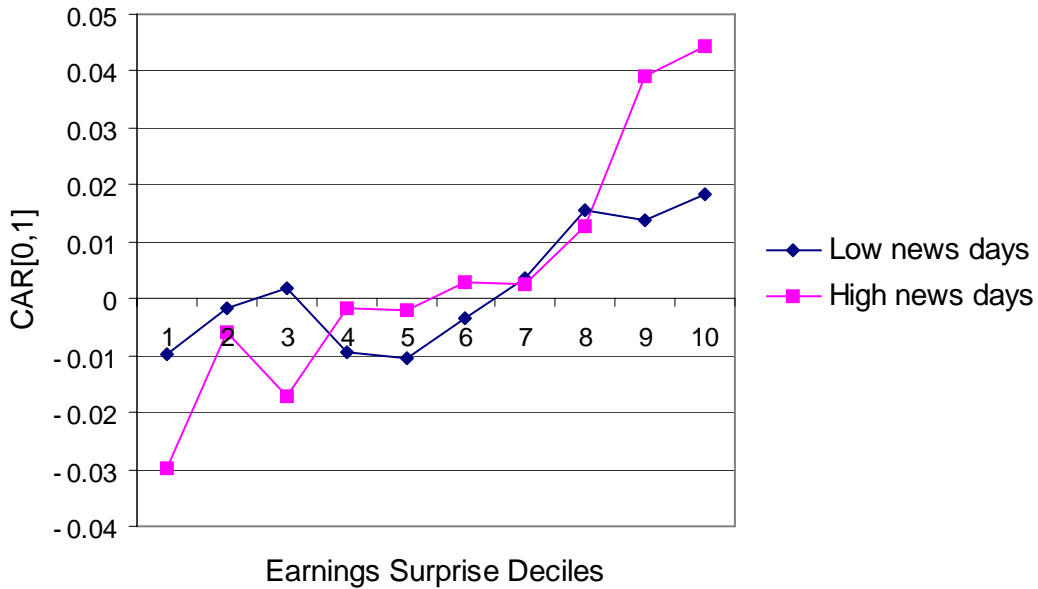


**Figure 2. Post-Earnings Announcement Drift: CAR[2,61]**

Figure 1 and Figure 2 show the average 2-day announcement cumulative abnormal returns (CAR[0,1]) and 60-day post-announcement cumulative abnormal returns (CAR[2,61]) of quarterly earnings announcements against earnings surprise deciles (1: bad news – 10: good news) for announcements on high-news days (number of announcements decile 10) and those on low-news days (number of announcements decile 1). Earnings surprise and number of announcement deciles are formed based on a quarterly independent double sort of quarterly earnings announcements by the corresponding forecast error and the number of quarterly earnings announcements on the day of announcement.

## Table 1.  Descriptive Statistics of Daily Number of Earnings Announcements

Quarterly earnings announcement dates are from CRSP-Compustat merged database and IBES for the period from January 1995 to December 2004.   We use the earnings announcement date from Compustat when the firm is not covered by IBES or when Compustat and IBES dates agree, and use the earlier date when Compustat and IBES announcement dates differ. Weekend earnings announcements are excluded from the sample.  The daily number of announcements is the total number of quarterly earnings announcements on each day.

### Panel A.  Distribution of Daily Number of Announcements

|       |          | *Percentiles* | | | | |
|-------|----------|-----|-----|--------|-----|-----|
| Mean  | Std. Dev | P10 | P25 | Median | P75 | P90 |
| 120.8 | 129.7    | 20  | 33  | 71     | 175 | 290 |

### Panel B.  Mean and Median Number of Announcements a Day, by Day of Week/Month/Year

|        | Monday | Tuesday | Wednesday | Thursday | Friday |
|--------|--------|---------|-----------|----------|--------|
| Mean   | 103.7  | 140.2   | 138.9     | 152.2    | 68.8   |
| Median | 62     | 78      | 77        | 90       | 53     |

|        | Jan   | Feb   | Mar  | Apr | May   | Jun  | Jul   | Aug   | Sep | Oct   | Nov   | Dec  |
|--------|-------|-------|------|-----|-------|------|-------|-------|-----|-------|-------|------|
| Mean   | 116.8 | 145.4 | 78.5 | 195 | 155.2 | 32.7 | 176.5 | 148.7 | 34  | 174.1 | 154.3 | 32.4 |
| Median | 86    | 147   | 68.5 | 142 | 123   | 30   | 122.5 | 107   | 32  | 128   | 118.5 | 31   |

|        | 1995  | 1996 | 1997  | 1998 | 1999  | 2000  | 2001  | 2002  | 2003  | 2004  |
|--------|-------|------|-------|------|-------|-------|-------|-------|-------|-------|
| Mean   | 100.4 | 107  | 112.4 | 117  | 121.3 | 145.5 | 138.1 | 130.9 | 120.4 | 114.5 |
| Median | 62    | 72   | 76    | 66   | 70    | 86.5  | 78    | 72    | 66    | 66    |

## Table 2. Firm Characteristics by the Number of Announcements Deciles

In each calendar quarter, we sort quarterly earnings announcements during that quarter with earnings surprise (forecast error), size, and book-to-market (B/M) information into deciles by the number of announcements on the day of the announcement. The number of announcements is the total number of quarterly earnings announcements by all firms covered by CRSP-Compustat on the same day. Table 2 reports the average size and B/M by the number of announcements deciles and the difference of size and B/M between deciles 10 and 1 with p-values. The size and B/M values are calculated at the end of June of each year based on the market value of equity at the end of June and the book value of equity for the last fiscal year end in the previous calendar year divided by the market value of equity for December of the previous calendar year.

|  | Size | B/M |
|---|---|---|
| Decile1 (low-news days) | 2347.1 | 0.662 |
| 2 | 2916.5 | 0.799 |
| 3 | 2347.8 | 0.946 |
| 4 | 2216.8 | 0.831 |
| 5 | 2718.9 | 0.756 |
| 6 | 3347.3 | 0.742 |
| 7 | 3076.7 | 0.714 |
| 8 | 3284.2 | 0.664 |
| 9 | 3434.4 | 0.679 |
| Decile10 (high-news days) | 3228.8 | 0.789 |
| Difference (10-1) | 881.7 | 0.127 |
| p-value | <0.001 | 0.128 |

**Table 3. Cumulative Abnormal Returns of Extreme Earnings Surprise Deciles
By Number of Announcements Deciles**

Using quarterly earnings announcements from January 1995 to December 2004, we calculate the average 2-day announcement cumulative abnormal returns (CAR[0,1]) and 60-day post-announcement cumulative abnormal returns (CAR[2,61]) for extreme earnings surprise deciles (FE10: good news, FE1: bad news) for each number of announcements deciles (NRANK).  Earnings surprise and number of announcement deciles are formed based on quarterly independent double sorts of quarterly earnings announcements by the corresponding forecast error and the number of quarterly earnings announcements on the day of announcement. The significance of the return spread between good and bad news firms (FE10-FE1) is marked by $^*$ (significant at 5%) and $^{**}$ (significant at 1%).

| NRANK | Average CAR[0,1] for Earnings surprise deciles 10 and 1 | | | Average CAR[2,61] for Earnings surprise deciles 10 and 1 | | |
|---|---|---|---|---|---|---|
| | FE1 | FE10 | FE10 −FE1 | FE1 | FE10 | FE10−FE1 |
| 1 (low-news days) | −3.27% | 3.81% | 7.07%$^{**}$ | −0.99% | 1.82% | 2.81% |
| 2 | −3.31% | 3.45% | 6.76%$^{**}$ | −1.67% | 3.10% | 4.77%$^{**}$ |
| 3 | −3.22% | 3.52% | 6.74%$^{**}$ | −2.09% | 2.09% | 4.18%$^{**}$ |
| 4 | −3.54% | 2.50% | 6.04%$^{**}$ | −4.79% | 3.25% | 8.04%$^{**}$ |
| 5 | −3.37% | 2.22% | 5.59%$^{**}$ | −2.19% | 2.24% | 4.43%$^{**}$ |
| 6 | −3.17% | 3.16% | 6.33%$^{**}$ | 0.96% | 4.17% | 3.21% |
| 7 | −3.67% | 2.82% | 6.49%$^{**}$ | −3.32% | 2.32% | 5.64%$^{**}$ |
| 8 | −3.45% | 2.79% | 6.24%$^{**}$ | −2.68% | 6.30% | 8.98%$^{**}$ |
| 9 | −3.49% | 2.83% | 6.32%$^{**}$ | −1.21% | 4.16% | 5.37%$^{**}$ |
| 10 (high-news days) | −3.06% | 2.61% | 5.67%$^{**}$ | −2.97% | 4.44% | 7.41%$^{**}$ |
| Difference (10−1) | 0.20% | −1.20%$^{**}$ | −1.40%$^*$ | −1.98% | 2.62% | 4.60%$^*$ |

# Table 4. Market Reactions to Earnings News: Regression Analysis

Table 4 reports the multivariate tests of the effects of the number of announcements on the relation between announcement and post-announcement returns and earnings surprises. FE is the earnings surprise deciles (FE=1: lowest, 10: highest) and NRANK is the number of announcement deciles based on quarterly independent sorts by forecast errors and the number of announcements on the day of announcement. SIZE is the size decile and BM is the book-to-market decile based on the most recent June size and book-to-market ratio of the firm using NYSE breakpoints, #Analysts is the number of analysts following the firm during the most recent fiscal year, LAG is the reporting lag defined as the number of days from the quarter end until the announcement date, and IO is the percentage of shares owned by institutions. Also included are year, month, and day of week dummies, and their interaction terms of FE. Standard errors adjusted for heteroskedasticity and clustering by the day of announcement are in parentheses ( $^*$ significant at 10%; $^{**}$ significant at 5%; $^{***}$ significant at 1%).

| | (1) CAR[0,1] | (2) CAR[0,1] | (3) CAR[0,1] | (4) CAR[0,1] | (5) CAR[2,61] | (6) CAR[2.61] | (7) CAR[2.61] | (8) CAR[2.61] |
|---|---|---|---|---|---|---|---|---|
| FE | 1.027$^{***}$ | 1.046$^{***}$ | 1.080$^{***}$ | 1.074$^{***}$ | 1.016$^{***}$ | 0.924$^{***}$ | 0.917$^{***}$ | 0.895$^{***}$ |
| | (0.070) | (0.071) | (0.073) | (0.072) | (0.239) | (0.244) | (0.250) | (0.251) |
| NRANK | 0.073$^{**}$ | 0.068$^{**}$ | 0.068$^{**}$ | 0.067$^{**}$ | −0.297$^{***}$ | −0.274$^{**}$ | −0.287$^{***}$ | −0.281$^{***}$ |
| | (0.031) | (0.032) | (0.031) | (0.031) | (0.108) | (0.108) | (0.107) | (0.108) |
| FE×NRANK | −0.021$^{***}$ | −0.024$^{***}$ | −0.030$^{***}$ | −0.029$^{***}$ | 0.049$^{***}$ | 0.064$^{***}$ | 0.066$^{***}$ | 0.070$^{***}$ |
| | (0.005) | (0.005) | (0.006) | (0.006) | (0.018) | (0.021) | (0.024) | (0.024) |
| SIZE | 0.267$^{***}$ | 0.267$^{***}$ | 0.267$^{***}$ | 0.267$^{***}$ | −0.012 | −0.014 | −0.013 | −0.014 |
| | (0.032) | (0.032) | (0.032) | (0.032) | (0.102) | (0.102) | (0.102) | (0.102) |
| FE×SIZE | −0.040$^{***}$ | −0.046$^{***}$ | -0.041$^{***}$ | −0.040$^{***}$ | −0.054$^{***}$ | −0.027 | −0.053$^{***}$ | −0.053$^{***}$ |
| | (0.005) | (0.006) | (0.005) | (0.005) | (0.016) | (0.020) | (0.016) | (0.016) |
| BM | 0.250$^{***}$ | 0.250$^{***}$ | 0.250$^{***}$ | 0.250$^{***}$ | −0.174$^{***}$ | −0.173$^{***}$ | −0.174$^{***}$ | −0.174$^{***}$ |
| | (0.020) | (0.020) | (0.020) | (0.020) | (0.067) | (0.067) | (0.067) | (0.067) |
| FE×BM | −0.034$^{***}$ | −0.034$^{***}$ | -0.034$^{***}$ | -0.034$^{***}$ | 0.015 | 0.015 | 0.015 | 0.015 |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.011) | (0.011) | (0.011) | (0.011) |
| LAG | 0.022$^{***}$ | 0.022$^{***}$ | 0.022$^{***}$ | 0.022$^{***}$ | 0.020 | 0.021 | 0.021 | 0.021 |
| | (0.005) | (0.005) | (0.005) | (0.005) | (0.017) | (0.017) | (0.017) | (0.017) |
| FE×LAG | −0.007$^{***}$ | −0.007$^{***}$ | −0.007$^{***}$ | −0.007$^{***}$ | −0.008$^{***}$ | −0.008$^{***}$ | −0.008$^{***}$ | −0.007$^{***}$ |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.003) | (0.003) | (0.003) | (0.003) |
| Log(1+#Analysts) | −0.437$^{***}$ | −0.437$^{***}$ | −0.436$^{***}$ | −0.437$^{***}$ | 1.496$^{***}$ | 1.496$^{***}$ | 1.494$^{***}$ | 1.497$^{***}$ |
| | (0.109) | (0.109) | (0.109) | (0.109) | (0.370) | (0.370) | (0.370) | (0.370) |
| FE×Log(1+#Analysts) | 0.051$^{***}$ | 0.051$^{***}$ | 0.023 | 0.052$^{***}$ | −0.153$^{***}$ | −0.153$^{***}$ | −0.101 | −0.154$^{***}$ |
| | (0.018) | (0.018) | (0.021) | (0.018) | (0.059) | (0.059) | (0.067) | (0.059) |
| IO | −1.255$^{***}$ | −1.255$^{***}$ | -1.256$^{***}$ | -1.254$^{***}$ | −0.200 | −0.199 | −0.198 | −0.203 |
| | (0.284) | (0.284) | (0.284) | (0.284) | (0.919) | (0.919) | (0.919) | (0.919) |
| FE×IO | 0.342$^{***}$ | 0.342$^{***}$ | 0.343$^{***}$ | 0.236$^{***}$ | 0.040 | 0.041 | 0.039 | 0.309 |
| | (0.046) | (0.046) | (0.046) | (0.058) | (0.146) | (0.146) | (0.146) | (0.203) |
| FE×NRANK×SIZE | | 0.001$^{*}$ | | | | −0.004$^{*}$ | | |
| | | (0.001) | | | | (0.002) | | |
| FE×NRANK ×Log(1+#Analysts) | | | 0.005$^{***}$ | | | | −0.009 | |
| | | | (0.002) | | | | (0.007) | |
| FE×NRANK×IO | | | | 0.019$^{***}$ | | | | −0.048 |
| | | | | (0.006) | | | | (0.029) |
| Calendar dummies, interacted with FE | X | X | X | X | X | X | X | X |
| Constant | −5.872$^{***}$ | −5.840$^{***}$ | −5.836$^{***}$ | −5.835$^{***}$ | −5.748$^{***}$ | −5.897$^{***}$ | −5.816$^{***}$ | −5.844$^{***}$ |
| | (0.436) | (0.437) | (0.436) | (0.436) | (1.535) | (1.538) | (1.534) | (1.535) |
| Observations | 117,640 | 117,640 | 117,640 | 117,640 | 116,414 | 116,414 | 116,414 | 116,414 |
| R-squared | 5.6% | 5.6% | 5.6% | 5.6% | 0.9% | 0.9% | 0.9% | 0.9% |

## Table 5.  Market Reactions to Earnings News: Additional Analysis

Table 5 reports the multivariate tests of the effects of the number of announcements on the relation between returns and earnings surprises. FE is the earnings surprise deciles (FE=1: lowest, 10: highest) and NRANK is the number of announcement deciles based on quarterly independent sorts by forecast errors and the number of announcements on the day of announcement.  Control variables include size deciles and book-to-market (B/M) deciles based on the most recent June size and book-to-market ratio of the firm using NYSE breakpoints, the number of analysts following the firm during the most recent fiscal year (log(1+# analysts following)), reporting lags (the number of days from the quarter end until the announcement date), the percentage of shares owned by institutions (institutional ownership), year, month, and day of week dummies, and interaction terms of FE with all control variables.  Standard errors adjusted for heteroskedasticity and clustering by the day of announcement are in parentheses ([*] significant at 10%; [**] significant at 5%; [***] significant at 1%).

|  | (1) CAR[-1,1] | (2) CAR[3,61] | (3) CAR[-30,-1] | (4) CAR[0,61] |
|---|---|---|---|---|
| FE | 1.154[***] | 1.100[***] | 1.796[***] | 2.117[***] |
|  | (0.075) | (0.235) | (0.161) | (0.255) |
| NRANK | 0.057[*] | −0.264[**] | 0.079 | −0.192[*] |
|  | (0.033) | (0.104) | (0.078) | (0.115) |
| FE×NRANK | −0.021[***] | 0.046[***] | −0.017 | 0.024 |
|  | (0.005) | (0.018) | (0.013) | (0.020) |
| Controls, interacted with FE | X | X | X | X |
|  |  |  |  |  |
| Constant | −5.907[***] | −6.052[***] | −5.197[***] | −11.911[***] |
|  | (0.472) | (1.500) | (0.969) | (1.575) |
| # Observations | 117,639 | 116,414 | 117,639 | 116,414 |
| R-squared | 5.8% | 0.9% | 2.5% | 2.1% |

Controls: Size and B/M deciles, log(1+# analysts following), reporting lags, institutional ownership, year, month, and day of week dummies. Interaction terms of FE with all control variables are also included.

## Table 6. Positive versus Negative Earnings Surprises

Table 6 reports multivariate tests of the effects of the number of announcements on the relation between returns and earnings surprises, separately for positive and negative earnings surprises. NRANK is the number of announcement deciles and FE is the earnings surprise quintile within each subsample of positive and negative surprises (FE = 1: lowest, 5: highest). Control variables include size deciles and book-to-market (B/M) deciles based on the most recent June size and book-to-market ratio of the firm using NYSE breakpoints, the number of analysts following the firm during the most recent fiscal year (log(1+# analysts following)), reporting lags (the number of days from the quarter end until the announcement date), the percentage of shares owned by institutions (institutional ownership), year, month, and day of week dummies, and interaction terms of FE with all control variables. Standard errors adjusted for heteroskedasticity and clustering by the day of announcement are in parentheses ($^{*}$ significant at 10%; $^{**}$ significant at 5%; $^{***}$ significant at 1%).

| | Positive Earnings Surprises | | | Negative Earnings Surprises | | |
|---|---|---|---|---|---|---|
| | CAR[0,1] | CAR[2,61] | CAR[0,61] | CAR[0,1] | CAR[2,61] | CAR[0,61] |
| FE | 1.475$^{***}$ | 0.957 | 2.582$^{***}$ | 0.538$^{**}$ | −1.133 | −0.277 |
| | (0.178) | (0.634) | (0.694) | (0.257) | (0.819) | (0.834) |
| NRANK | 0.032 | −0.345$^{**}$ | −0.292$^{**}$ | −0.005 | −0.593$^{***}$ | −0.526$^{**}$ |
| | (0.039) | (0.135) | (0.147) | (0.067) | (0.224) | (0.233) |
| FE×NRANK | −0.039$^{***}$ | 0.120$^{**}$ | 0.074 | 0.015 | 0.156$^{***}$ | 0.153$^{**}$ |
| | (0.013) | (0.049) | (0.055) | (0.018) | (0.059) | (0.061) |
| Controls, interacted with FE | X | X | X | X | X | X |
| Constant | −2.401$^{***}$ | −0.528 | −3.173 | −5.224$^{***}$ | −1.581 | −7.779$^{**}$ |
| | (0.532) | (1.921) | (2.055) | (0.955) | (3.146) | (3.187) |
| # Observations | 64,231 | 63,643 | 63,643 | 36,584 | 36,064 | 36,064 |
| R-squared | 2.0% | 1.1% | 1.7% | 2.0% | 1.6% | 1.5% |

Controls: Size and B/M deciles, log(1+# analysts following), reporting lags, institutional ownership, year, month, and day of week dummies. Interaction terms of FE with all control variables are also included.

# Table 7: Trading Volume Response to Earnings News

We perform multivariate analysis of the effect of competing annoucements on trading volume response to earnings news. The dependent variable is one- or two-day abnormal trading volume (VOL[0], VOL[0,1]). Abnormal trading volume on a given day is defined as the log dollar trading volume on that day normalized by the average log dollar trading volume over days [-41,-11] of the announcement. VOL[0] is the abnormal trading volume on the announcement date and VOL[0,1] is the average abnormal trading volume over days [0,1] of the announcement. AFE is the absolute earnings surprise deciles and NRANK is the number of announcements deciles based on quarterly independent sorts by absolute forecast errors and the number of announcements on the day of announcement. Regressions (3) and (6) use indicator variables for each earnings surprise deciles. MKTVOL is the market abnormal trading volume on the announcement date and MKTVOL2 is the 2-day market abnormal trading volume over days [0,1] of the announcement. Other control variables include size and book-to-market (B/M) deciles based on the most recent June size and book-to-market ratio of the firm using NYSE breakpoints the number of analysts following the firm during the most recent fiscal year (log(1+# analysts following)), reporting lags (the number of days from the quarter end until the announcement date), the percentage of shares owned by institutions (institutional ownership), year, month, and day of week dummies. Standard errors adjusted for heteroskedasticity and clustering by the day of announcement are in parentheses ($^*$ significant at 10%; $^{**}$ significant at 5%; $^{***}$ significant at 1%).

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | VOL[0] | VOL[0] | VOL[0] | VOL[0,1] | VOL[0,1] | VOL[0,1] |
| AFE | 0.031$^{***}$ | 0.031$^{***}$ | | 0.030$^{***}$ | 0.029$^{***}$ | |
| | (0.002) | (0.002) | | (0.001) | (0.001) | |
| NRANK | −0.022$^{***}$ | −0.028$^{***}$ | −0.028$^{***}$ | −0.022$^{***}$ | −0.029$^{***}$ | −0.029$^{***}$ |
| | (0.002) | (0.003) | (0.003) | (0.002) | (0.002) | (0.002) |
| Dummy variables for FE deciles | | | X | | | X |
| MKTVOL | | 0.779$^{***}$ | 0.781$^{***}$ | | | |
| | | (0.044) | (0.043) | | | |
| MKTVOL2 | | | | | 0.818$^{***}$ | 0.820$^{***}$ |
| | | | | | (0.046) | (0.046) |
| Controls | | X | X | | X | X |
| Constant | 0.470$^{***}$ | 0.634$^{***}$ | 0.686$^{***}$ | 0.530$^{***}$ | 0.718$^{***}$ | 0.794$^{***}$ |
| | (0.016) | (0.036) | (0.038) | (0.014) | (0.032) | (0.034) |
| # Observations | 117,640 | 117,640 | 117,640 | 117,640 | 117,640 | 117,640 |
| R-squared | 0.7% | 3.0% | 3.0% | 1.0% | 4.2% | 4.4% |

Controls: Size and B/M deciles, log(1+# analysts following), reporting lags, institutional ownership, year, month, and day of week dummies.

## Table 8: Fama-French Alphas of Post-Earnings Announcement Drift Portfolios

At the end of each month from March 1995 until December 2004, we independently sort stocks into 5x5 groups based on their most recent quarterly earnings surprises within the last three months (FE=1~5) and the number earnings announcements on the day of earnings announcement (NRANK=1~5). We calculate equally-weighted returns of the resulting 5x5 portfolios during the following month. Within each of number of announcements rank (NRANK), we form a hedge portfolio that is long in good news portfolio (FE=5) and short in bad news portfolio (FE=1) to exploit post-earnings announcement drifts. Alphas from time-series regressions of portfolio monthly returns (less the risk-free rate except for the zero-cost hedge portfolios) on Fama-French three factors are reported with Newey-West standard errors with 12 lags are in parentheses ($^*$ significant at 10%; $^{**}$ significant at 5%; $^{***}$ significant at 1%). The first row reports the alphas of the base post-earnings announcement drift portfolios equally weighting firms in each earnings surprise quintile. The last row reports the alphas of hedge portfolios long in high-news day portfolio (NRANK=5) and short in the low-news day portfolio (NRANK=1) within each earnings surprise quintile.

| | Earnings Surprise Quintile | | | | | |
| | FE=1 (Bad news) | 2 | 3 | 4 | FE=5 (Good news) | FE5-FE1 (Good −Bad) |
|---|---|---|---|---|---|---|
| All | −0.57 | −0.53$^{***}$ | −0.12 | 0.04 | 0.75$^{***}$ | 1.32$^{***}$ |
| | (0.36) | (0.20) | (0.14) | (0.14) | (0.26) | (0.26) |
| NRANK 1 | −0.21% | −0.53$^{**}$ | −0.17 | 0.04 | 0.56$^{**}$ | 0.77 |
| | (0.42) | (0.22) | (0.21) | (0.21) | (0.24) | (0.47) |
| 2 | −1.10$^{***}$ | −0.56$^{**}$ | −0.04 | −0.23 | 0.45 | 1.55$^{***}$ |
| | (0.37) | (0.24) | (0.21) | (0.18) | (0.28) | (0.26) |
| 3 | −0.51 | −0.61$^{***}$ | 0.02 | −0.02 | 0.70$^{**}$ | 1.22$^{***}$ |
| | (0.43) | (0.23) | (0.17) | (0.15) | (0.30) | (0.37) |
| 4 | −0.16 | −0.56$^{**}$ | −0.26 | 0.32 | 0.94$^{***}$ | 1.09$^{***}$ |
| | (0.50) | (0.25) | (0.16) | (0.20) | (0.34) | (0.40) |
| NRANK 5 | −0.60$^{*}$ | −0.44$^{***}$ | −0.15 | 0.06 | 1.04$^{***}$ | 1.64$^{***}$ |
| | (0.34) | (0.17) | (0.14) | (0.17) | (0.34) | (0.31) |
| NRANK5 – NRANK1 | −0.38 | 0.09 | 0.03 | 0.02 | 0.48$^{*}$ | 0.86$^{*}$ |
| | (0.33) | (0.16) | (0.20) | (0.21) | (0.24) | (0.47) |

# Table 9: The Effect of Related vs. Unrelated Announcements

We examine the effect of the number of related and unrelated announcements on the 2-day announcement cumulative abnormal returns (CAR[0,1]) and the 60-day post-announcement cumulative abnormal returns (CAR[2,61]). We calculate the daily number of quarterly earnings announcements for each industry using Fama-French 10 industry classification. The number of related announcements is the number of quarterly earnings announcements by the same industry firms, and the number of unrelated announcements is the number of quarterly earnings announcements by firms in other industries. FE is the earnings surprise deciles (FE=1: lowest, 10: highest) based on quarterly sorts by forecast errors using all observations, and NrelRank/NunrelRank is the decile rank of the number of related/unrelated announcements (10: highest, 1: lowest) announcements based on quarterly sorts by the number of related/unrelated announcements within each industry. We exclude firms in Industry 10 ('Others'). Control variables include size deciles and book-to-market (B/M) deciles based on the most recent June size and book-to-market ratio of the firm using NYSE breakpoints, the number of analysts following the firm during the most recent fiscal year, reporting lags (the number of days from the quarter end until the announcement date), the percentage of shares owned by institutions (institutional ownership), year, month, and day of week dummies, and interaction terms of FE with all control variables. Standard errors adjusted for heteroskedasticity and clustering by the day of announcement are in parentheses ($^{*}$ significant at 10%; $^{**}$ significant at 5%; $^{***}$ significant at 1%).

|  | (1) CAR[0,1] | (2) CAR[0,1] | (3) CAR[0,1] | (4) CAR[2,61] | (5) CAR[2,61] | (6) CAR[2,61] |
|---|---|---|---|---|---|---|
| FE | 0.976$^{***}$ | 1.019$^{***}$ | 1.022$^{***}$ | 0.907$^{***}$ | 0.741$^{***}$ | 0.748$^{***}$ |
|  | (0.075) | (0.079) | (0.079) | (0.252) | (0.271) | (0.270) |
| NrelRank | 0.063$^{**}$ |  | 0.010 | −0.244$^{**}$ |  | -0.044 |
|  | (0.032) |  | (0.039) | (0.105) |  | (0.141) |
| FE×NrelRank | −0.015$^{***}$ |  | −0.004 | 0.026 |  | -0.011 |
|  | (0.005) |  | (0.006) | (0.017) |  | (0.022) |
| NunrelRank |  | 0.092$^{**}$ | 0.084$^{*}$ |  | −0.355$^{***}$ | −0.321$^{*}$ |
|  |  | (0.036) | (0.046) |  | (0.123) | (0.165) |
| FE×NunrelRank |  | −0.021$^{***}$ | −0.018$^{**}$ |  | 0.052$^{**}$ | 0.061$^{**}$ |
|  |  | (0.006) | (0.007) |  | (0.021) | (0.028) |
| Controls, interacted with FE | X | X | X | X | X | X |
| Constant | −5.941$^{***}$ | −6.154$^{***}$ | −6.163$^{***}$ | −5.765$^{***}$ | −4.939$^{***}$ | −4.921$^{***}$ |
|  | (0.470) | (0.492) | (0.493) | (1.658) | (1.761) | (1.760) |
| Observations | 92,685 | 92,685 | 92,685 | 91,737 | 91,737 | 91,737 |
| R-squared | 5.7% | 5.7% | 5.7% | 1.1% | 1.1% | 1.1% |

Controls: Size and B/M deciles, log(1+# analysts following), reporting lags, institutional ownership, year, month, and day of week dummies. Interaction terms of FE with all control variables are also included.