Media Coverage and Investors' Attention to Earnings Announcements

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Abstract

Does inattention cause the post-earnings announcement drift? We study this question using media coverage as a proxy for investor attention. We compare announcements made by the same firm in the same year and generating the same earnings surprise (as measured by the gap between the median analyst forecast and reported earnings), when one announcement receives more media coverage than the other (as measure by the number of *Wall Street Journal* articles covering the announcement). We find that announcements with more media coverage generate a stronger price and trading volume reaction at the announcement and less subsequent drift. Moreover, this effect is less pronounced for more visible firms (as proxied by age and market-to-book), on high-distraction days (as proxied by the number of firms in the media at the time of the announcement) and for sophisticated investors (as proxied by trade size or the fraction of individual shareholders). These results are both economically and statistically strong. Our results lend support to the notion that limited attention is an important source of friction in financial markets.

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1. Introduction

Underreaction to corporate events – defined as average post-event abnormal returns of the same sign as event-date returns – is a pervasive anomaly in financial markets. Prominent examples include dividend initiations and omissions, stock splits, earnings announcements, changes in analyst recommendations and in capital structure such as tender offers and seasoned equity offerings.[1] Various explanations for the return drift following these events have been put forward, some risk-based and others behavioral. One explanation that has recently generated interest holds that it is caused by investors' lack of attention. If inattentive investors only gradually learn about an event – and if market frictions prevent attentive investors from arbitraging the mispricing away, then returns will display continuations.

Inattention is a simple and appealing explanation. It is an inexorable implication of our limited cognitive resources: we simply cannot process the many signals we receive and need to focus on a selected few at the expense of the others. Recent theories flesh out the implications of these limitations, which range from mispricing to comovements in asset returns or in volatility.[2] Though these limitations seem obvious, evidence is still scarce on how inattention shapes investors' decisions and equilibrium outcomes.

In this paper, we assess empirically whether inattention leads investors to underreact to earnings news. We focus on earnings announcements because they are not the most likely candidate for inattention-driven underreaction. Not only are earnings announcements highly relevant to firm valuation, they are also regular and often scheduled in advance, offering investors ample opportunity to react adequately. We use media coverage as a proxy for

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[1] For dividend initiations and omissions, see Michaely (1995); for stock splits, see Ikenberry and Ramnath (2002); for earnings announcements, see Bernard and Thomas 1990); for changes in analyst recommendations, see Womack (1996) and Michaely and Womack (1999); for tender offers, see Ikenberry (1995); for seasoned equity offerings, see Loughran and Ritter (1995).
[2] See for example Sims (2003), Hirshleifer and Teoh (2003), Peng (2005) and Peng and Xiong (2006).

investors' attention, and measure it as the number of articles published about the announcing firm in the *Wall Street Journal* (WSJ) at the time of the announcement. We examine whether the post-earnings announcement drift is caused by (a lack of) media coverage.

The essence of our results is captured in Figure 1. The figure displays the evolution of the average cumulative abnormal return in event-time relative to the earnings announcement date for two pairs of announcements. Each pair consists of quarterly announcements made by the same firm in the same year and generating the same surprise (as measured by the gap between the median analyst forecast and reported earnings). One receives more coverage from the WSJ (solid curves) than the other (dashed curves).[3] Importantly, this matching procedure ensures that any effect we capture reflects the impact of media coverage rather than variations in firm characteristics. For example, market capitalization has an overwhelming impact on both media coverage and the post-earnings announcement drift. If we did not control for it, we could wrongly interpret a size effect as a media, i.e. attention, effect.[4]

The top two curves in Figure 1 refer to positive earnings surprises and the bottom two cures to negative surprises – again the magnitude of the surprise is similar within each pair of announcements. The plot clearly shows that announcements with more media coverage generate less post-earnings announcement drift – the solid lines are flatter than the dashed lines over the post-announcement window. Media coverage increases the 70-day cumulative abnormal return by 5.8% for announcements in the bottom surprise decile (bad surprise) and decreases it by 3.7% for those in the top decile (good surprise). These effects are not only statistically strong, they are also economically large: the drift is eliminated

[3] As a matter of fact, in 90% of pairs, one announcement is reported in the WSJ while the other is not. In the remaining 10%, one announcement is reported in the WSJ on both the announcement day and the day that follows, while the other is reported only on one day.

[4] Covered firms tend to be large (Fang and Peress (2007)) and large firms tend to have less post-earnings drift (Bernard and Thomas (1989)). Other characteristics include liquidity, the book-to-market ratio, analyst following, the fraction of individual ownership and the sector in which firms operate.

altogether for negative surprises and halved for positive surprises. Our results therefore demonstrate that attention is an important driver of the post-earnings announcement drift.[5][6]

According to the attention hypothesis, the drift is reduced because investors react more strongly to the earnings news when it is released. This is indeed what the picture shows. Announcements with more media coverage are associated with a stronger reaction over a window that covers the pre-announcement period and the announcement itself (from day -30 to day +1). The economic magnitude of this effect is large and commensurate to that observed in the post-announcement period. The 32-day cumulative abnormal return is lower by 2.2% for announcements in the bottom earnings surprise decile and larger by 2.1% for those in the top decile. Interestingly, the timing of the attention effect differs across negative and positive earnings surprises. While it is concentrated on the announcement date for negative surprises, it is spread over the pre-announcement period for positive surprises – in fact the return response on the announcement day is similar for positive surprises whether they are covered in the media or not. As we examine in more detail these two kinds of announcements, we find that positive announcements with a WSJ article on the announcement day tend to have significantly more articles also during the pre-announcement period. This is not the case for negative announcements. One interpretation is that managers release information about forthcoming announcements early when it is positive, consistent with Hong et al. (2002)'s finding that "bad news travels slowly".[7]

[5] Our analysis accounts for the endogeneity of media coverage – media coverage tends to be larger for more surprising announcements. Indeed, it does not test whether announcement covered in the media trigger a stronger market response but whether, for these announcements, the *sensitivity* of the market reaction to earnings news is larger. Moreover, any alternative explanation for the attenuated drift we document under more intense media coverage must also explain why we find a magnified reaction in return and trading volume at the announcement.

[6] Whether media draws attention to announcements or whether it simply proxies for attention, i.e. the investors' attention is drawn to an announcement by an exogenous event that also catches the media's interest, has no bearing on our conclusion. Both interpretations, causality vs. correlation are consistent with theories of attention.

[7] Hong et al. (2002)document that momentum strategies work particularly well among stocks with low analyst following (holding size fixed), and that the effect of analyst coverage is much more pronounced for stocks that are past losers than for stocks that are past winners, suggesting that good news, unlike bad news, is disclosed quickly by managers.

We also investigate the influence of media coverage on the volume response to the announcement. We find that trading volume, measured at the announcement, is larger for announcements with more media coverage, especially when the earnings surprise is negative. Thus, our findings provide some support for the use of trading volume as a proxy for investor attention.[8]

Having established that the market response to earnings announcement is related to investors' attention – as proxied by their coverage in the media, we attempt to identify characteristics of announcement days and announcing firms for which this effect is the strongest. A regression analysis reveals that the effect of media coverage on abnormal returns is significantly weaker for older firms and on high-news days. That is, older firms and high-news days are associated with a weaker response at the announcement and a stronger response in the subsequent period. The effect on trading volume is more pronounced for stocks with a higher fraction of individual ownership and for small trades. Focusing on small trades, we find that the effect is weaker for glamour firms and on high-news days.

These results lend support to the notion that inattention tones down investors' immediate reaction to earnings announcements and accentuates their delayed reaction. If investors are more distracted at certain times, such as when there are many firms in the news, then the occurrence of WSJ articles will overestimate how much attention is really paid to announcements. Similarly, some firms such as older firms which are established and well known, or glamour firms (firms with a high market-to-book ratio) which have grown strongly in recent years may be repeatedly on investors' minds, so variations in media coverage overstate differences in attention to these firms. Such times and firms should therefore be associated with a weaker effect of media coverage, as we report. Finally, we expect the effect of attention to be more pronounced for stocks held and traded predominantly by investors who are more attention-constrained, such as individual

[8] More precisely, we show that low trading volume signals that investors are inattentive. But we do not show the converse, that high trading volume implies that investors are attentive. For example, intense trading could be a sign of strong disagreement among few investors. Because of its availability, trading volume is often used to measure investors' attention (e.g. Gervais et al. (2001), Frazzini and Lamont (2006), Hou et al. (2006), Barber and Odean (2007)).

investors. To summarize, we find that media coverage has less influence for more visible firms, on high-distraction days and for institutional investors, in agreement with the attention hypothesis.

Finally, we assess the economic importance of the attention effect by studying the profitability of a strategy that "sells the drift" when the announcement receives attention and "buys the drift" when it does not. We form a high-attention portfolio that buy firms whose most recent announcement was in the top earnings surprise quintile and was covered in the WSJ, and sells short firms whose most recent announcement was in the bottom quintile and was covered in the WSJ. We form a low-attention portfolio in a similar fashion, except that we only use firms whose most recent announcement was not covered in the WSJ. A strategy that is long the low-attention portfolio and short the high-attention portfolio yields a sizeable risk-adjusted return of 9.6% per annum (statistically significant at the 1% level). We emphasize that our portfolio formation approach is implementable as it only makes use of data that is available on the formation date and of stocks that are relatively liquid and easy to short (our sample consists mostly of NYSE stocks with at least one analyst).

Our findings contribute to the recent but growing empirical literature on the role of attention. It relates most closely to DellaVigna and Pollet (2006), Hirshleifer et al. (2006) and Hou et al. (2006) who also study investors' response to earnings announcements using various proxies for attention. DellaVigna and Pollet (2006) report that the post-earnings announcement drift increases while the announcement-event return and trading volume decrease when the announcement is made on a Friday. Hirshleifer et al. (2006) find a similar pattern for announcements made on days when there are numerous news releases by other firms. Hou et al. (2006) show that earnings momentum is reduced for stocks with high trading volume and in up markets. We provide consistent evidence based on a different proxy for attention – media coverage. As in DellaVigna and Pollet (2006) and Hirshleifer et al. (2006), our proxy has the advantage of being unrelated to the trading process. A further benefit is that it can be measured over various windows to capture time variations in attention to a given earnings announcement. For example, it reveals that attention increases in the days that precede the announcement if the news is positive but not if it is negative. A final contribution of this paper is to use a matching procedure that controls for a host of firm characteristics. Specifically, because we compare announcements made by the same firm in the same year, our procedure controls for *all* firm characteristics, including those that are unobserved, that do not vary from one announcement to another within the year.[9] Other studies use media coverage as we do to proxy for attention, albeit not to analyze earnings announcements.[10] We add to these papers by presenting comprehensive evidence that media coverage influences the market's reaction to earnings announcements.

The balance of the paper is organized as follows. Section 2 reviews the related literature. Section 3 develops the test hypotheses and statistical methodology. Section 4 describes the data and variable definitions. Section 5 presents the results. We start with a preliminary analysis that does not control for firm characteristics (Section 5.1) and move on to a matching procedure that does so (Section 5.2). Then, we perform a regression analysis to identify the circumstances under which attention effects are the strongest (Section 5.3). Finally, we study the profitability of a trading strategy based on our findings (Section 5.4). Section 6 concludes.

2. Related literature

A growing strand of research studies the role of attention in economics.[11] On the theory side, models have been developed to flesh out its implications. For example, Sims (2003) studies its effect on price and consumption dynamics, and Mankiw and Reis (2002) and Woodford (2002) on monetary transmission mechanisms. Hirshleifer and Teoh (2003) examine the influence of attention on firms' accounting disclosure policies, and Peng (2005) and Peng and Xiong (2006) on the correlations in stock return. Hong and Stein (1999) assume that private information diffuses gradually across a population of

[9] DellaVigna and Pollet (2006) and Hirshleifer et al. (2006) control for an explicit list of firm characteristics by including them as explanatory variables in their regression analysis.
[10] See for example Klibanoff, Lamont and Wizman (1998), Huberman and Regev (2001) , Nofsinger (2001), Meschke (2002).
[11] See Hirshleifer et al. (2006) for a review of the psychological literature on attention.

"newswatchers" to explain short run underreaction and long run reversals. Gabaix and Laibson (2003) and Gabaix et al. (2006) present and test in an experimental setting a tractable model of attention allocation.

Empirically, attention has been shown to influence a number of trade and return patterns. These include momentum and reversals in stock returns (Hou et al. (2006)), the gradual diffusion of information across stocks or sectors (Hong, Torous and Valkanov (2005), Hou and Moskowitz (2005), Cohen and Frazzini (2006)), investors' propensity to trade (Barber and Odean (2007)), the premium associated with extreme trading activity (Gervais et al. (2001)) and with earnings announcements (Frazzini and Lamont (2006)).

Our paper is most closely related to studies of investors' attention to earnings announcements (DellaVigna and Pollet (2006), Hirshleifer et al. (2006) and Hou et al. (2006)). DellaVigna and Pollet (2006) report that the post-earnings announcement drift increases while the announcement-event return and trading volume decrease when the announcement is made on a Friday. They also show that managers take advantage of investors' distraction by releasing worse news on Fridays. Hirshleifer et al. (2006) find a similar return and volume pattern for announcements made on days when there are numerous news releases by other firms. They further show that the pattern is reversed if competing announcements are made by firms operating in the same industry as the announcing firm, indicating that these related announcements attract rather than distract attention to the announcing firm. Hou et al. (2006) find that earnings momentum is reduced for stocks with high trading volume and in up markets, which proxy for attention – investors are more attentive in up markets and increased attention leads to more trading. In contrast to earnings momentum profits, price momentum profits reverse in the long run, and increase with trading volume. This indicates that enhanced attention can also induce overreaction.

Several studies use media coverage as a proxy for attention, albeit not to study earnings announcements. In an interesting case in point, Huberman and Regev (2001) report that in 1998 an article in the *Sunday New York Times* on a new drug triggered a large market reaction though the news had already been reported in the journal *Nature* and various popular newspapers several months ago. Klibanoff, Lamont and Wizman (1998) measure the elasticity of closed-end country fund prices to asset value. They document that its magnitude is larger and closer to one when country news appears on the front page of *The New York Times*. Meschke (2002) analyzes price and volume reactions to CEO interviews broadcast on CNBC. He documents positive abnormal returns and trading volume before and during the interview though it does not convey any new information. Barber and Odean (2007) show that individual investors are net buyers of stocks mentioned on the Dow Jones newswire. Nofsinger (2001) compares the trading behavior of institutional and individual investors around news releases in the *Wall Street Journal*. He finds that longer articles induce individuals, but not institutions, to trade more.

3. Methodology

We describe in turn the test hypotheses, the estimation procedure and the data.

3.1 Hypothesis development

We state our main hypotheses and then flesh out their implications for certain groups of investors, days and types of firms.

Main hypotheses

We postulate that the coverage of earnings announcements in the media is positively correlated to the attention they attract from investors. This leads to the following testable hypotheses.

Hypothesis 1: The sensitivity of announcement abnormal returns to earnings surprises rises with media coverage.

Hypothesis 2: The sensitivity of post-announcement abnormal returns to earnings surprises declines with media coverage.

Hypothesis 3: Abnormal trading volume at the announcement rises with media coverage.

Under hypotheses 1 and 3, announcements that draw more attention as proxied by their coverage in the media, generate a stronger immediate reaction in the market both in terms of returns and volume. Hypothesis 2 states that these stronger immediate reactions lead to less drift over the subsequent period. A rejection of any of these hypotheses implies no influence of attention, as proxied by media coverage.

Of course, media coverage is not exogenous – it tends to be larger for more newsworthy or surprising announcements. So announcements with media coverage are naturally associated with a stronger market reaction, both at the time of the announcement and over the subsequent period. For this reason, we control for the importance of earnings surprises throughout our analysis. That is, we do not test whether announcements covered in the media trigger a stronger market response. Rather, we test whether, for these announcements, the *sensitivity* of the market reaction to earnings news is larger.

Moreover, supposing we did not control for the importance of the surprise, a positive correlation between media coverage and the importance of the surprise, while consistent with hypotheses 1 and 3, would lead to a rejection of hypothesis 2. Indeed bigger surprises generate *more* drift, not less (Bernard and Thomas (1989)), so announcements covered in the media, in the absence of any other effect, would be followed by more drift, not less.

If hypotheses 1 to 3 are not rejected, then we attempt to identify the conditions under which attention has the strongest influence. Specifically, we examine whether it is more pronounced for certain groups of investors (hypotheses 4 to 6 pertaining to sophisticated vs. unsophisticated investors), on particular days (hypothesis 6 on high- vs. low- distraction days) and for certain types of firms (hypothesis 7 on firm visibility).

Attention and investor types

It is plausible that attention is more limited for individual investors than for professional investors such as institutions (Barber and Odean (2007))[12]. If this is the case, then attention will have a stronger impact on the trading behavior of individuals and on the stocks they predominantly own. We assess this possibility using the fraction of individual ownership and trade size as proxies for investor sophistication – individuals tend to trade in smaller amounts. We formulate the following hypotheses.

Hypothesis 4a: The effect of media coverage on announcement and post-announcement abnormal returns and on abnormal trading volume is stronger for firms with a higher fraction of individual ownership.

Hypothesis 5a: The effect of media coverage abnormal trading volume is stronger for small trades than for large trades.

Alternatively, Bernard and Thomas (1990) argue that the post-earnings announcement drift is caused by unsophisticated investors such as individuals.[13] If they trade in a contrarian fashion – selling (buying) in response to good (bad) earnings news, then they will slow down the incorporation of earnings news into stock prices and induce a post-earnings announcement drift. If individuals indeed cause the drift and the drift is reduced by attention, that is hypothesis 3 is not rejected, then it is possible that more visible announcements attract proportionally more institutional attention, i.e. that attention is

[12] Barber and Odean (2007) study how trades of individual and institutional investors respond to attention-grabbing events. They find that individual investors tend to be net buyers of stocks that are in the news, stocks experiencing high abnormal trading volume, and stocks with extreme one day returns.

[13] Bernard and Thomas (1990) conjecture that some investors use a naïve seasonal random walk model to predict earnings, i.e. extrapolate earnings from the same quarter in the previous year. The evidence on the role of unsophisticated investors is mixed. The evidence on their conjecture is mixed so far. Potter (1992) documents that the return response to earnings announcements is dampened for firms held by fewer individuals (and hence fewer institutions) but Bartov et al. (2000) find mixed results on the post-earnings announcement drift. Lee (1992), Bhattacharya (2001) and Battalio and Mendenhall (2005) find evidence that this the case using trade size as a proxy for investor sophistication. But Hirshleifer et al. (2003), examining the actual trades of individuals from a large discount broker, find no such evidence.

actually more scarce for institutions than individuals.[14] This would lead to the opposite of hypotheses 4a and 5a, as stated in the following hypotheses.

Hypothesis 4b: The effect of media coverage on announcement and post-announcement abnormal returns and on abnormal trading volume is stronger for firms with a lower fraction of individual ownership.

Hypothesis 5b: The effect of media coverage abnormal trading volume is stronger for large trades than for small trades.

A rejection of hypotheses 4a, 4b, 5a and 5b could occur either because sophisticated and unsophisticated investors are equally attracted to announcements with high media coverage, or because the fraction of individual ownership and trade size are poor proxies for sophistication.

Barber and Odean (2007) also develop a variant of these hypotheses for investors subject to short-sales constraints. They argue that news that attracts their attention induces them to buy even if the news is bad, because only investors who own the stock can actually sell it.[15] In that case, attention should have a stronger effect on positive earnings surprises – since it causes both constrained and unconstrained investors to buy, than on negative earnings surprises – for which it induces unconstrained investors to sell and constrained investors to not trade or buy. This notion is formalized in the next hypothesis.

Hypothesis 6: The effect of media coverage on announcement and post-announcement abnormal returns and on announcement trading volume is stronger for positive earnings surprises than for negative earnings surprises.

[14] As an example of attention effects among professional traders, Corwin and Coughenour (2005) document that NYSE specialists have limited attention and that it influences the execution quality of the stocks in which they make markets.

[15] Constrained investors may include some individuals and some institutions such as mutual funds which are not allowed to short. Hirshleifer et al. (2006) document that the number of competing earnings announcement has an effect for positive earnings surprise but not for negative surprises. They interpret this asymmetry as supportive of the Barber and Odean (2007) hypothesis. Hou, Peng and Xiong (2006) also find evidence of an asymmetric effect of attention.

Attention and distracting events

If investors are more distracted at certain times, such as when the weekend approaches or when there are many firms in the news, then the occurrence of WSJ articles may overestimate how much attention is really paid to announcements.[16] Such times should therefore be associated with a weaker effect of media coverage:

Hypothesis 7: The effect of media coverage on announcement and post-announcement abnormal returns and on abnormal trading volume is stronger on high-distraction days.

They find that individual investors tend to be net buyers of high attention stocks, defined as those in the news, those experiencing high abnormal trading volume, and those with extreme one day returns

Attention and firm visibility

Similarly, some firms may be constantly on investors' minds so media coverage does not really reflect attention to these firms. These include large firms, old firms – well known and established, firms followed by many analysts, firms operating in the technology sector – our sample period covers the technology boom and bust when much attention was paid to technology firms, and growth or glamour firms – with a low book-to-market ratio. The effect of media coverage should again be smaller for these highly visible firms. This leads to the following hypothesis.

Hypothesis 8: The effect of media coverage on announcement and post-announcement abnormal returns and on abnormal trading volume is stronger for less visible firms.

We describe next the estimation procedure.

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[16] DellaVigna and Pollet (2006) and Hirshleifer et al. (2006) show respectively that investors pay less attention to a firm's announcement on Fridays and when there are simultaneously numerous news releases by other firms.

3.2 Estimation procedure

We measure the sensitivity of abnormal returns and trading volume to earnings surprises, and examine how it is affected by media coverage. As a warm-up, we perform an unconditional analysis, i.e. we do not control for other possible determinants of this sensitivity. Specifically, we assign announcements to groups based on how surprising they are and on how much media attention they receive. Then we examine how the market's reaction – announcement and post-announcement abnormal returns and announcement abnormal trading volume – differs across media groups belonging to the same surprise groups. Importantly, we check that within surprise groups, announcements are similar in terms of the magnitude of the surprise. If this were not the case, any difference between covered and non-covered announcements belonging to the same surprise group could result from differences in the size of the surprise rather than in media coverage.

While the unconditional analysis is informative, it does not guarantee that effects we may capture reflect the impact of media coverage rather than variations in some firm characteristics. For example, market capitalization is a firm characteristic that has an overwhelming impact on both media coverage and the post-earnings announcement drift. It is well known that covered firms tend to be large and that large firms tend to have less post-earnings drift (Bernard and Thomas (1989)). So a potential media effect may in fact be a size effect in disguise. Other relevant characteristics include liquidity, the book-to-market ratio, analyst following, the fraction of individual ownership and the sector in which firms operate.[17] To factor out firm characteristics, the next step of our analysis uses a matching procedure.

Our strategy is to compare earnings announcements that are made by the same firm but that differ in the amount of media coverage they receive. We form pairs of announcements according to the following criteria:

[17] Bernard and Thomas (1989), Potter (1992), Bhushan (1994) and Vega (2006) show respectively that size, institutional ownership, liquidity and analyst following are drivers of the post-earnings announcement drift. Fang and Peress (2007) document that media coverage increases in size, liquidity and analyst following and decreases in individual ownership.

1. The announcements are made by the same firm in the same calendar year.
2. The announcements belong to the same surprise deciles.
3. In each pair, one announcement receives more media coverage than the other.

If we find more than two announcements satisfying these requirements (e.g. more than one announcement without media coverage), then we take the average over the candidate announcements. Requirement 1 guarantees that the paired announcements correspond to the same firm. Since the longest time interval between matched announcements is three quarters, neither firm characteristics nor the market have time to change significantly. Requirement 2 ensures that the paired announcements are similar in surprise magnitude. Finally, requirement 3 introduces differences in media coverage across the paired announcements.

4. Data and variable definitions

We describe in turn how we measure media coverage, earnings surprises and abnormal returns and trading volume.

4.1 Media coverage

Our proxy for the amount of attention an earnings announcement attracts from investors is the number of articles published about the announcing firm in the *Wall Street Journal* (WSJ) at the time of the announcement. We choose the WSJ because it is a specialized financial daily newspaper with a broad coverage of the market and a wide circulation.[18] We obtain the data from LexisNexis, an online database.[19] Our initial sample of firms consists

[18] The WSJ is the second most circulated daily paper in the U.S and is read by both professional individual investors. Its average weekday circulation is over 1.8 million copies in 2002 (excluding online subscriptions, data from the Audit Bureau of Circulations). The daily newspaper with the highest circulation is *USAToday*.
[19] LexisNexis uses an indexing technology to associate articles to company names. The list of company names, which includes all firms listed on the NYSE and NASDAQ exchange, is obtained from LexisNexis and matched to the CRSP companies' names. The CRSP names differ slightly from the LexisNexis names because of abbreviations or special characters (such as spaces, &, ‘ or -). A computer program is used for matching, and the remaining names are matched manually.

of all companies listed on the NYSE and 500 randomly selected companies listed on the NASDAQ between January 1, 1993 and December 31, 2002.[20]

Earnings announcements are usually reported in the WSJ on the following day. Figure 2 displays the fraction of firms featured in the WSJ in event time relative to their announcement date (day 0). The fraction increases nine fold to 0.149 on day 1 from an average of 0.017 on the other days. This reflects the fact that the WSJ is printed and distributed in the morning, before the day's announcements are made. A t-test and a non-parametric Wilcoxon (Mann-Whitney) rank-sum test both indicate that the fraction of covered firms is also significantly larger on day 0, suggesting that on some occasions the WSJ reports earnings-related news before their release. Our analysis groups together articles published on days 0 and 1. For simplicity, we refer to them as "announcement-day" articles.[21]

4.2 Earnings

Data on quarterly earnings announcements – announcements dates and analysts earnings forecasts – are obtained from IBES from 1993 to 2002 for every firm in our sample.[22] We estimate the earnings surprise as the difference between the announced earnings and the consensus earnings forecast, normalized by the share price (Kothari (2001), DellaVigna and Pollet (2006), Hirshleifer et al. (2006)). The consensus forecast is defined as the median forecast among all the analysts who issue or review a forecast in the last 2 months before the earning announcement. If an analyst makes multiple forecasts over that interval, we use only the most recent one. Specifically, denoting E_{iq} the earnings per share announced by firm i in quarter q, F_{iq} the corresponding consensus forecast, and P_{iq} the share price at the end of the announcement month, we define the earnings surprise SUR_{iq} as:

[20] Stocks trading in any sub-period within the 10-year period, such as those listed after January 1, 1993 and those de-listed before December 31, 2000, are kept in the sample.

[21] Our data identifies whether a company is mentioned in the WSJ on a given day. It does not guarantee that articles are specifically about its earnings. However, an inspection of the data reveals that in virtually all cases, articles published on the announcement day or the day that follows refer to the announcement. Articles published when exchanges are closed are aggregated with those observed on the first subsequent trading day, if any.

[22] DellaVigna and Pollet (2006) check the accuracy of earnings announcement dates provided by IBES and conclude that it is "almost perfect after December 1994".

$$SUR_{iq} = \frac{E_{iq} - F_{iq}}{P_{iq}}$$

Earnings, forecasts and prices are split-adjusted. We eliminate penny stocks (observations with a share price, unadjusted for splits, below 1$) and observations with actual earnings or consensus earning forecast exceeding the stock price.

4.3 Abnormal returns and trading volume

Daily stock returns and trading volume are downloaded from CRSP. To account for return premia associated with size, book-to-market and momentum, we adjust stock returns using the characteristic-based matching procedure in Daniel, Grinblatt, Titman, and Wermers (1997) and Wermers (2004). We use this approach rather than the Fama-French four-factor model (augmented with Carhart (1997)'s momentum factor) because Daniel and Titman (1997) find that characteristics rather than estimated covariances explain better the cross-section of stock returns in the post-1963 period.

We estimate cumulative abnormal returns before, at and after the announcement. The announcement abnormal cumulative return is defined as the abnormal return from the close of the trading day before the announcement to the close of the trading day after , i.e. over days 0 and 1, and is denoted $CAR[0,1]_{iq}$ for firm i in quarter q**.** This measure captures the immediate response to announcements made during trading hours and after the market closes. The pre- and post-announcement abnormal cumulative returns, denoted $CAR[-30,-1]_{iq}$ and $CAR[2,71]_{iq}$, are defined respectively as the abnormal returns over the windows [-30,-1] and [2,71]. We use a 70 trading-day window because most of the drift occurs in the three months following announcements (Bernard and Thomas (1989)). We drop announcements with fewer than 20 daily return observations in the two months that either precede or follow the announcement.

To estimate abnormal trading volume, we compute the difference between the average daily number of shares traded at the announcement (days 0 and 1) and the average daily number of shares traded over the pre-announcement (days -30 to -1) and divide it by their sum. We also break up trading volume into small and large trades. Data on transactions is downloaded from the Trade And Quote (TAQ) dataset. Trades are classified by size using a variation of the Lee (1992) firm-specific dollar based trade-size proxy, described in Hvidkjaer (2006). The procedure sorts stocks into quintiles based on NYSE/AMEX firm-size cut-off points and uses the following small- (large-) trade cut-off points within firm-size quintiles: $3,400 ($6.800) for the smallest firms, $4,800 ($9.600), $7,300 ($14.600), $10,300 ($20,600) , and $16,400 (32,800) for the largest firms.

4.4 Other data

We obtain market capitalization, and trading volume data from CRSP, and accounting data, such as book value of assets, from Compustat. The market and book values of equity are measured at the end of the previous calendar year. Size is defined as the log of the market value of equity. Age is measured as the log of the number of years since the firm's first appearance on the CRSP tapes. Turnover is defined as the log of the ratio of the number of shares traded during a year to the number of shares outstanding. Liquidity is measured using the Amihud (2002) illiquidity ratio and equals the ratio of a stock's absolute return to its dollar trading volume in a day, averaged over all days in a year. We also estimate the fraction of individual ownership for each stock and year as one minus the fraction of total institutional ownership, obtained by aggregating 13f filings.

4.5 Descriptive statistics

Our final sample includes 2 508 firms and 54 582 announcements. Panel A of Table 1 displays some descriptive statistics on announcing firms. As expected given our sample formation, the average firm is relatively large with a market capitalization that exceeds a billion dollars ($1,136 million) and visible with a mean (median) number of analysts of 7 (5) and about half of its shares held by individuals. Panel B provides some statistics on the coverage of earnings announcements in the WSJ. Most announcements are not reported in the WSJ. Only 16% are covered on either day 0 or day 1 and 1% are covered on both days.

We note before turning to the results, that our sample is biased towards firms whose returns exhibit less drift. Indeed, our media data covers mostly NYSE firms and we require at least one analyst forecast from IBES. These constraints tend to rule out the smaller and less followed firms for which future returns are more predictable (Bernard and Thomas (1990), Bushan (1994)).

5. Results

As a preliminary analysis, we examine the relation between media coverage and the market reaction to earnings surprises unconditionally, i.e. without controlling for other possible determinants of this sensitivity. Then, we use a matching procedure to factor out firm characteristics. We also perform a regression analysis to identify the circumstances under which the media has the strongest influence. Finally, we discuss the profitability of trading strategies based on our findings.

5.1 Unconditional analysis of the full sample

In each calendar quarter, we perform a two-way independent sort of all quarterly earnings announcements into 2 x 10 = 20 groups based on the coverage of the announcement in the WSJ (*MEDIA*) and the earnings surprise (*SUR*). Media group 1 (*MEDIA*1) contains announcements that are covered by the WSJ on the announcement day or the day that follows, and media group 0 (*MEDIA*0) contains the remaining announcements, that is announcements with no WSJ coverage on these days. Earnings surprise deciles are numbered in increasing order from the most negative surprises (*SUR*1) to the most positive (*SUR*10). In most of our analysis, we focus on extreme earnings surprises (*SUR*1 and *SUR*10), where the post-earnings announcement drift has been found to be the strongest (Bernard and Thomas (1989, 1990)). This reduces the noise stemming from observations with modest surprises and little drift (Hirshleifer et al. (2006)).

Before we can move on to analyzing returns, we need to ensure that within each earnings surprise deciles, media groups contain observations that are similar in terms of the magnitude of the surprise. If the earnings surprise groups are too few, and the WSJ focuses its coverage on the more surprising announcements, then the size of the surprise will be larger in media group 1 than in media group 0. In this case, any return differential between covered and non-covered announcements belonging to the same surprise group could result from differences in the size of the surprise rather than in media coverage. Table 2 shows that this is not a concern with surprise deciles. The magnitude of the surprise is not significantly different across the media groups. The difference across the 2 groups has a t-stat of 0.7 in the most positive surprise decile (*SUR*10) and of -0.3 in the most negative surprise decile (*SUR*1). [23] Thus, within surprise deciles, media groups contain announcements with similar surprise sizes, and sorts by media coverage within surprise deciles are not further sorts by the magnitude of the surprise. We can now proceed to an examination of returns.

Return response

We estimate the average announcement-day and post-announcement cumulative abnormal returns, *CAR*[0,1] and *CAR*[2,71], in each group. Table 2 (Panel A) reports the returns for the most positive (*SUR*10) and the most negative earnings surprise deciles (*SUR*1), as well as the difference in returns across the two extreme earnings surprise deciles. These differences capture the market's reaction to the earnings news. The difference in *CAR*[0,1] measures the immediate response to the announcement – a more positive difference corresponding to a stronger response. Similarly, the difference in *CAR*[2,71] measures the drift following the announcement. This time, a more positive difference indicates a stronger drift or more underreaction to the news when it is announced, i.e. good (bad) news is followed by positive (negative) abnormal returns.

Table 2 reveals that investors' immediate reaction to earnings announcements is stronger when the announcement is covered in the WSJ. The difference in *CAR*[0,1] between the most positive (*SUR*10) and the most negative earnings surprise deciles (*SUR*1) rises from

[23] This finding is further confirmed by a non-parametric test (not reported). A median test rejects with a p-value of 0.78 the hypothesis that covered announcements are associated with a more negative surprise in the most negative decile (*SUR*1). Similarly, it rejects with a p-value of 0.69 that they are associated with a more positive surprise in the most positive decile (*SUR*10).

4.1% to 5.6% when the news is mentioned in the WSJ (the difference 1.6% is strongly statistically significant with a t-stat of 3.9). Figure 3 illustrates these findings. It displays daily abnormal returns over a 10-day window that straddles the announcement for both covered and uncovered announcements in both extreme surprise deciles.

Table 2 also shows that media coverage eliminates the post-announcement drift. The difference in *CAR*[2,71] drops from 3.9% to 1.7% which is not significantly different from zero. The difference, -2.2%, is moderately statistically significant with a t-stat of 1.8. The magnitude of the drift for no-media announcements is consistent with previous findings (Bernard and Thomas (1990)).

Volume response

Panel B of Table 2 reports the average volume response to announcements. Trading volume surges upon an announcement in both extreme surprise deciles regardless of whether the announcement is covered in the media (abnormal trading volume is significantly positive in media groups 0 and 1). But it grows more for covered announcements. Abnormal trading volume is larger by 86% (= 0.101/0.118) in the most negative earnings surprise decile (*SUR*1) and by 45% (= 0.075/0.167) in the most positive decile (*SUR*10) when the announcement is reported in the WSJ. These effects are strongly statistically significant with t-stats of 7.3 and 5.9. They are illustrated in Figure 4 which plots daily abnormal trading volume over a 10-day window that straddles the announcement for both covered and uncovered announcements. The difference in abnormal volume is large on days 0 and 1 and then dies out. It is also large on days -2 and -1 suggesting some front-running of the announcement. A closer inspection of the data indicates that front-running mostly happens for positive surprises (see discussion below).

Our findings so far show that media coverage magnifies the market reaction on the announcement day and reduces the subsequent drift. But this analysis does not control for firm characteristics that correlate with media coverage. So we cannot be sure that the return differentials we report reflect the impact of media coverage rather than variations in some firm characteristics. As Table 3 shows, various firm characteristics vary strongly with the coverage of earnings announcements in the WSJ. The table indicates that, in comparison to non-covered announcements, covered announcements are made by larger and more liquid firms, firms with a higher book-to-market ratio (value stocks, but this effect is only statistically significant for positive surprises), firms more closely followed by analysts, firms with a lower fraction of individual ownership and firms operating in the technology sector.[24] Since many of these characteristics also influence the post-earnings announcement drift, it is essential to control for them in order to isolate the impact of media coverage.[25] We take on this task in the next section.

5.2 Matching announcements

We use a matching procedure to control for firm determinants in assessing the impact of the media coverage. We form pairs of quarterly announcements made by the same firm in the same year and belonging to the same surprise decile. Within each pair, one announcement receives more media coverage on the announcement day or the day that follows (solid curves) than the other (dashed curves).

Table 4 provides some descriptive statistics on the matches. Panel A shows that most pairs consist of one announcement receiving coverage while does not. Only 10% (= 184 / 1854) of pairs are covered on both announcements, i.e. consist of one announcement covered on both day 0 and day 1 and one announcement covered on a single day (day 0 or day 1). Since each pair contains an announcement that receives media coverage, the characteristics of matched announcements are comparable to those obtained for the full sample. Indeed, the characteristics of announcing firms displayed in Panel B of Table 4 are similar to those in the covered announcements (*MEDIA*1 row) in Table 3. They are particularly large with an average market capitalization of 3.15 billion dollars.

[24] To classify firms in our sample as tech or non-tech stocks, we use the list of tech SIC codes and Internet IPOs in Loughran and Ritter (2004). Tech firms include Internet firms (such as e-commerce firms).

[25] Bernard and Thomas (1989), Potter (1992), Bhushan (1994) and Vega (2006) show respectively that size, institutional ownership, liquidity and analyst following are drivers of the post-earnings announcement drift.

Our focus is on differences between the more covered and the less covered announcements that comprise a pair, which we denote with a prefix Δ. For example, $\Delta CAR[0,1]$ refers to the difference in $CAR[0,1]$ within pairs, namely $CAR[0,1]$ for the high-coverage announcement minus $CAR[0,1]$ for the low-coverage announcement.

As we did for the analysis of the full sample, we start by making sure that there is no perceptible difference in the magnitude of the surprise across the paired observations. Pane C of Table 4 reports the spread in surprise across the matched announcements for the two extreme surprise deciles. It indicates that they are not significantly different from zero (the t-stats are -1.1 in the most negative (*SUR*1) and 0.1 in the most positive (*SUR*10)).[26] We can therefore rest assured that any difference in returns we may find is not driven by a difference in the size of the earnings surprise.

Return response

We turn to the analysis of returns in Table 5. The first panel reports the difference in announcement-day abnormal returns between paired observations, $\Delta CAR[0,1]$. It reveals that the influence of media coverage on the immediate reaction to announcements varies across surprise deciles. In the most negative surprise decile (*SUR*1), the presence of a WSJ article increases the immediate market response to the news – it reduces the abnormal return by 2.4% (the t-stat is -2.7). In contrast, it has no significant influence (the t-stat is 0.6) in the most positive surprise decile (*SUR*10). The third column of the table displays the "difference in the difference", i.e. the spread in the media impact across the two extreme surprise deciles, i.e. the spread in the return difference within a pair of announcements. It equals 2.1% and is statistically significantly (the t-stat equals 1.8), indicating that WSJ coverage considerably magnifies the announcement return response.

Table 5 also shows the results for the post-announcement drift. In contrast to the announcement-day reaction, media coverage has a strong effect on the drift in both extreme

[26] This finding is again confirmed non-parametrically. A median test of the hypothesis that the surprise difference across paired announcements, ΔSUR, equals zero is not rejected with p-values of 0.42 in *SUR*1 and 0.78 in *SUR*10.

surprise deciles. It increases the 70-day cumulative return by 5.8% (the t-stat is 2.6) in the most negative surprise decile (*SUR*1) and decreases it by 3.7% (the t-stat is 1.8) in the most positive decile (*SUR*10). The difference in differences displayed in the last column is large, 9.4% and strongly significant (the t-stat is -3.1). These effects are economically large. The drift is eliminated altogether for negative surprises and halved for positive surprises.[27] These findings indicate that investors' inattention, as reflected by the absence of a WSJ article on the announcement day, is an important driver of the drift.

Thus, we confirm our previous finding that media coverage strongly reduces the post-earnings announcement drift. But we find that its impact on investors' immediate reaction is more nuanced: it magnifies the announcement-day return only in the most negative surprise decile. Hirshleifer et al. (2006) also report evidence for an asymmetric attention effect using the total number of earnings announcements made on the same day. But in contrast to our results, they find that more attention – as proxied fewer competing announcements, increases the announcement response and reduces the drift for good news only.[28]

To shed light on this disparity, we examine the market's behavior in the period that precedes the earnings announcement. Table 5 reports the within-pair difference in abnormal returns measured over a 30 trading day period before the announcement (from day -30 to -1 relative to the event), $\Delta CAR[-30,-1]$. An asymmetry across the surprise deciles is again apparent, but this time media coverage has a significant impact in the most positive surprise

[27] For announcements in the bottom surprise decile, the drift equals -4.4% under low media coverage (with a t-stat of 2.7) vs. 1.4% (with a t-stat of 0.8) under high media coverage. For announcements in the top surprise decile, the drift equals 6.7% under low media coverage (with a t-stat of 4.5) vs. 3.1% (with a t-stat of 2.0) under high media coverage.

[28] Hirshleifer et al. (2006) explain their result by appealing to the argument in Barber and Odean (2007) that attention-grabbing events such as extreme earnings news generate on average more buys than sells from individual investors. Indeed, these investors choose which stocks to buy from a universe of thousands of stocks but, because of short-sell constraints, select which stocks to sell from those they already own. Thus, both positive and negative earnings news that attract their attention leads to buys. These buys reinforce those of unconstrained investors (also drawn to the event) in the case of positive news, but offset the sells of unconstrained investors in the case of negative news. This results in a strong effect of attention for positive news and a muted effect for negative news.

decile (*SUR*10) only. In this decile, the presence of a WSJ article on the day of or following the announcement is associated with an increase in the pre-announcement period abnormal return of 2.5% (the t-stat is 1.8). There is no such influence in the most negative decile (*SUR*1) (the t-stat is -0.1).

In the last panel of Table 5, we sum the abnormal return earned upon the announcement with that earned over the pre-announcement period, i.e. we consider cumulative abnormal returns from day -30 to day +1 relative to the announcement event, ΔCAR[-30,1]. The table no longer displays any asymmetry between positive and negative surprise. The return differences are similar in absolute value (-2.2% in *SUR*1 and 2.1% in *SUR*10) but not statistically significant (the t-stats are -1.4 in *SUR*1 and 1.4 in *SUR*10). Their difference across the two extreme surprise deciles however is strongly statistically significant (the t-stat is 2.0). Moreover its magnitude normalized by the duration of the period (4.3% over 31 days) is roughly similar to that of the post-earnings announcement drift (9.4% over 69 days).

These findings suggest that the reason announcement-day returns in the most positive decile are not sensitive to the presence of a WSJ article is that for covered announcements, stock prices have already adjusted to the earnings news in the pre-announcement period.

Table 5 also provides information concerning a potential asymmetry across surprise deciles. The statistics displayed in the last column of the panels show whether the impact of media coverage is stronger in the top or the bottom surprise decile. There appears to be no significant difference, except over the announcement window [0,1] but this difference vanishes once we merge it with the pre-announcement window, [-30,1]. If anything, the evidence on ΔCAR[-30,1] and ΔCAR[2,71] suggests that the effect of media coverage is more pronounced for negative surprises than for positive surprises (the estimate in the *SUR*1 + *SUR*10 column is positive for ΔCAR[-30,1] and negative for ΔCAR[2,71], albeit not significantly). The absence of an asymmetry across surprise deciles cast doubt on hypothesis 6 on the interplay between attention and short-sales constraints.

Together, our analysis of returns reveals that announcements covered in the WSJ are related to less drift, whether the earnings news is good or bad. Moreover, negative surprises covered in the WSJ are associated with a stronger market reaction on the announcement day, while positive surprises covered in the WSJ are associated with a stronger market reaction over a period that precedes the announcement. But we find no difference in the effect of media coverage across extreme surprise deciles when returns are measured over the [-30,1] or [2,71] windows. Thus, the evidence is consistent with hypotheses 1 and 3 but not with hypotheses 6.

These results are illustrated in Figure 1. It displays cumulative abnormal returns in event time for the two announcements in a matched pair (announcements with high coverage are represented by the solid lines, and those with low coverage by the dashed lines) and for the most negative and positive earnings surprises (respectively in the upper part of the picture in green, and in the lower part in red). The plot clearly shows the following feature.[29]

- Pre-announcement return: Positive announcements with high media coverage on the day of the announcement are associated with positive abnormal returns over the period that precedes the announcement – the upward sloping solid green line from day -30 to -1. This is neither the case for positive announcements with low media coverage, nor for negative announcements.
- Announcement return: All announcements, except those associated with a negative surprise and low media coverage, see a strong return reaction on the day of the announcement – the jumps on day 0. In contrast to negative surprises, the announcement returns for positive surprises seem no different across the paired announcements.
- Post-announcement return: Finally, returns drift less when there is a WSJ article on the announcement day – the solid lines are flatter than the dashed lines over the post-announcement period.

[29] The picture is qualitatively identical when we drop pairs of announcements in which one announcement is covered on both day 0 and day 1 and the other is covered on day 0 or 1 (10% of pairs).

We also find some evidence of an asymmetry in media coverage between the two extreme surprise deciles during the pre-announcement period, in line with abnormal returns. Table 6 shows the difference in media coverage across paired announcements, $\Delta MEDIA$[-30,-1], where media coverage is measured as the average number of WSJ articles published about the firm in the pre-announcement window. In the most positive surprise decile (*SUR*10), announcing firms with a WSJ article on the announcement day tend to have significantly more articles also during the pre-announcement period (the t test is 3.3). This is not the case in the most negative surprise decile (*SUR*1). [30] This effect is of an interesting economic magnitude. Announcements that are not covered on the announcement day have a 3.3% probability of receiving coverage on any given day of the [-30,-1] window (whether they are in the top or bottom surprise decile). If they are covered, then the probability grows by 9% to 3.6% for announcements in the bottom decile and by 30% to 4.3% for announcements in the top decile.

One interpretation is that information about forthcoming positive surprises leaks out early on to the press, and is capitalized into stock prices before the release date. The asymmetry between good and bad news is consistent with Hong et al. (2002)'s finding that "bad news travels slowly". They document that momentum strategies work particularly well among stocks with low analyst following (holding size fixed), and that the effect of analyst coverage is much more pronounced for stocks that are past losers than for stocks that are past winners, suggesting that good news, unlike bad news, is disclosed quickly by managers.

Table 6 also reports the difference in media coverage at the announcement, $\Delta MEDIA$[0,1], and over the post-announcement period, $\Delta MEDIA$[2,71]. As expected given our matching procedure, the difference in media coverage at the announcement equals 0.5 and is strongly significant. More interestingly, there is no perceptible difference in media coverage over

[30] These findings are confirmed non-parametrically. In the most positive surprise decile (*SUR*10), a median test rejects the null that the pre-announcement amount of media coverage is identical across the paired announcement with a p-value of 0.015. For negative surprises in contrast, the p-value is 0.66 so there is no significant difference within pairs.

the period that follows the announcement. This finding lends support to the notion that the post-announcement drift is driven by an underreaction to the announcement on the announcement day that slowly corrects, rather than by some overreaction over the post-announcement period.

Volume response

To measure the volume difference across paired announcements, we compute the difference in the average daily number of shares traded at the announcement (days 0 and 1) between the high- and low-coverage announcements, and divide it by their sum.[31] We denote it ΔVOL. We carry out a similar analysis breaking up trades into small and large. $\Delta SMALL\_VOL$ and $\Delta LARGE\_VOL$ denote respectively the difference in the average daily number of shares traded in small transactions, respectively large transactions, between the high- and low-coverage announcements, divided by their sum

The results displayed in Table 7 are consistent with those of the full sample and hypothesis 3: Overall trading volume is larger for announcements with more media coverage. This effect is strong for announcements in the lowest surprise decile (*SUR*1 where the t-stat is 3.1) but weak for those in the highest surprise decile (*SUR*10 where the effect is positive but not significantly different from zero with a t-stat of 0.2). This asymmetry is also consistent with the estimates obtained for the full sample (Panel B of Table 2) where abnormal trading volume grows with media coverage, but 35% (= (0.101 – 0.075) / 0.075) more so for announcements in *SUR*1 than for those in *SUR*10. The difference across surprise deciles is only significant for small trades (with t-stat of 2.9). These findings reject hypothesis 6 that posits a weaker attention effect for negative surprises.

Moreover, there is no perceptible difference between small and large trades (the t-stats on the difference are 1.3 and -1.0 in *SUR*1 and *SUR*10 respectively). Thus, hypotheses 4a and 4b that individual investors trade differently from institutions on attention-drawing events find no support. To the extent that trade size is a valid proxy for investor sophistication, this

[31] The results are similar when we measure trading volume over the [-30,1] window.

finding suggests that attention is a scarce resource both for sophisticated and unsophisticated investors.

The next section considers the role of characteristics of announcement days and firms. In particular, it complements the analysis of trade size with the fraction of individual ownership.

Regression analysis

Having established that the market response to earnings announcement is related to the coverage of announcements in the media – a proxy for investors' attention, we attempt to identify the characteristics of announcement days and announcing firms for which this effect is the strongest.

There may be times when investors are more distracted, for example when the weekend approaches or when many firms are in the news. Indeed, DellaVigna and Pollet (2006) and Hirshleifer et al. (2006) show respectively that investors pay less attention to announcements when they occur on Fridays and when there are simultaneously numerous news releases by other firms. In such times, the occurrence of WSJ articles may overestimate how much attention is really paid to announcements. They should be therefore associated with a weaker effect of media coverage. We construct proxies for investors' distraction. We count the total number of firms mentioned in the WSJ around each earnings announcement (on days 0 and 1), which we denote *Other_News.* We define Δ*Other_News* as the difference in the log of *Other_News* across matched announcements (high-media minus low-media). Similarly, we construct a dummy variable *Friday* that equals 1 if the earnings announcement happens on a Friday and 0 otherwise and define Δ*Friday* as the difference in the *Friday* dummy across matched announcements (high-media minus low-media).

It is also plausible that some firms such as larger and older firms are constantly on investors' minds. For these firms, variations in media coverage across matched announcements may not reflect significant differences in attention, i.e. these variations may overstate the true differences in attention. If this is the case, the effect of media coverage should be smaller for these more visible firms. Variables associated with the visibility of announcing firms are size and age – larger and older firms are better known, book-to-market – low book-to-market firms are growth and glamour firms[32], analyst following, and whether they operate in the technology sector – our sample period is marked by the technology boom and bust which drew much attention from investors.[33] To complement our comparison of small and large trades, we also study whether the fraction of individual ownership exerts an influence on returns and trading volume as stated in hypotheses 4a and 4b.

We investigate whether the impact of media coverage on the market's reaction to earnings announcements is reduced on high-distraction days – days with many firms in the news and Fridays, for more visible firms – larger, older, low book-to-market and technology firms, and for firms held by more individual investors. In our analysis, we control for liquidity because it is an important determinant of the post-earnings announcement drift (Mendenhall (2004), Sadka (2006), Chordia et al. (2007)). We use two proxies for liquidity: the share turnover defined as the log of the ratio of the number of shares traded during a year to the number of shares outstanding, and Amihud (2002)'s illiquidity ratio measured as the log of the ratio of a stock's absolute return to its dollar trading volume in a day, averaged over all days in a year.[34]

[32] Glamour stocks have very high valuations relative to their assets. They are mostly stocks of companies whose earnings have grown strongly over the previous years.

[33] Peng and Xiong (2006) show theoretically that limited attention leads to category-learning behavior, i.e. attention-constrained investors tend to allocate more attention to sector-level factors than to firm-specific factors. This behavior is consistent with the finding in Cooper et al. (2001) that firms that added a "dot.com" suffix to their name during the tech bubble without fundamentally changing their strategies earned significant abnormal returns around their name-change announcements.

[34] The Amihud illiquidity ratio captures the absolute percentage price change per dollar of trading volume, i.e., the price impact of trades, and is correlated with illiquidity proxies obtained from microstructure data (see Amihud (2002)).

We carry out a regression analysis on the two extreme surprise deciles. We define a dummy variable D that equals 1 for announcements in the top decile $SUR10$, and 0 for announcements in the bottom decile $SUR1$. We run the following regressions for cumulative abnormal returns:

$$\Delta CAR = a_0 + a_1 D + \sum_{j=1}^{n} b_j (D \times X_j) + \sum_{j=1}^{n} c_j X_j + \sum_{k=1}^{m} d_k C_k + \sum_{k=1}^{m} e_k (D \times C_k) ,$$

where ΔCAR refers to $\Delta CAR[0,1]$ or $\Delta CAR[2,71]$, the X_j denote characteristics of announcements ($\Delta Other\_News$ and $\Delta Friday$) and of announcing firms (size, age, book-to-market, analyst following, tech and the fraction of individual ownership), and the C_k denote control variables (turnover and Amihud illiquidity ratio). The coefficients of interest are the b_j. They capture the impact of the characteristics X_j on the difference in ΔCAR across extreme surprise deciles ($SUR10$ - $SUR1$). For example, a positive slope b_j in the $\Delta CAR[0,1]$ regression indicates that the effect of media coverage on immediate abnormal returns is strengthened for high values of the variable X_j, i.e. that media coverage is more closely associated with attention when X_j is high. Since a stronger return reaction upon announcement corresponds to less drift over the subsequent period (Table 5), we expect the estimated coefficient on the same variable in the $\Delta CAR[2,71]$ regression to be negative. Therefore, we look for variables that, when interacted with the dummy D, have coefficient estimates significantly different from zero and of opposite sign across the $\Delta CAR[0,1]$ and $\Delta CAR[2,71]$ regressions.

We estimate a similar regression for trading volume, except that we no longer need the interacted terms:

$$\Delta VOL = \alpha_0 + \alpha_1 D + \sum_{j=1}^{n} \beta_j X_j + \sum_{k=1}^{m} \gamma_k C_k .$$

A positive coefficient β_j in the ΔVOL regression implies that media coverage increase trading volume more when the variable X_j is high, controlling for the factors in C_k. We also break down trading volume into small and large trades and run the same regression. In both the return and volume regressions, we report *p*-values based on robust standard errors clustered by firm.

Return response

The results are presented in Table 8. Panel A displays the estimates for the return regressions. The only interacted variables that come up with significantly opposite signs in the return regressions are Δ*Other_News* and age. The coefficient estimates on Δ*Other_News* are negative in the Δ*CAR*[0,1] regression (the p-value is 0.081) and positive in the Δ*CAR*[2,71] regression (the p-value is 0.092). These estimates indicate that the publication of a WSJ article about an announcement increases the immediate market response and reduces the subsequent drift less on days with many firms in the media, i.e. that the impact of the article is reduced on days with much distracting news. This effect is economically large: a one standard deviation increase in Δ*Other_News* (= 0.208, which corresponds to a 23% increase in the ratio of the number of firms mentioned in the WSJ around the high-coverage announcement to the number of firms mentioned around the low-coverage announcement) leads to a 1.83%(= 0.208 x 0.088) fall in Δ*CAR*[0,1] and a 4.6% (= 0.208 x 0.223) increase in Δ*CAR*[2,71]. Given the estimates of Table 5, such an increase in Δ*Other_News* wipes out the media effect at the announcement and halves it over the post-announcement window.

Firm age is a firm characteristic that displays a similar pattern across the Δ*CAR* regressions. The coefficient estimate on *Age* x *D* is positive in the Δ*CAR*[0,1] regression (the p-value is 0.096) and negative in the Δ*CAR*[2,71] regression (the p-value is 0.001). Thus, the impact of media coverage is more pronounced (stronger immediate response and weaker drift) for younger firms. This effect is also economically large: a one standard deviation increase in ln(*Age*) (= 1.001, which corresponds to an increase in age by a factor 2.7) leads to a 2.30% (= 1.001 x 0.023) fall in Δ*CAR*[0,1] and a 11.3% (= 1.001 x 0.113) increase in Δ*CAR*[2,71].

The other interacted variables are not significant at conventional levels.[35]

Volume response

Panel B of Table 8 displays the estimates for the volume regressions. The fraction of individual ownership and turnover are the only significant regressors in the ΔVOL regression. The coefficient estimates are positive in both cases, indicating that attention has a stronger impact on firms held by more individuals and on more liquid firms. The impact if individual ownership is also economically large: a one standard deviation increase in the fraction of individual ownership (= 0.271) leads to a 7.5% (= 0.271 x 0.278) increase in ΔVOL. As a comparison, it corresponds to more than half of the average volume effect (taking the average ΔVOL in *SUR*1 and *SUR*10 is 12.6% in Table 7).

The regressions for small and large trades and their difference are instructive. The results for large trades are by and large similar to those obtained for all trades. But those for small trades reveal a strongly negative effect of Δ*Other_News* and a marginally positive effect of book-to-market (p-value = 0.101). They indicate that a WSJ article increases small trades but less so on days with much distracting news and for glamour or growth firms. The Friday dummy Δ*Friday* is negative in line with the distraction hypothesis of DellaVigna and Pollet (2006) but not significantly so.

The dummy *D* is marginally negative in the ΔVOL regression (p-value is 0.103) and strongly negative in the Δ*SMALL_VOL* regression, suggesting that attention increases trading volume more in response to bad news than to good news, especially for small trades. This confirms that hypothesis 6 is rejected. The intercept in the Δ*SMALL_VOL* –

[35] It may not be so surprising that the number of analyst does not come out significant given that all the firms in our sample are followed by at least one analyst. It is possible that what matters to a firm's visibility are not how many analysts cover it but whether or not it is covered. Hong, Lim and Stein (2002) for example find that analysts speed up the flow of information but at a decreasing rate.

Δ*LARGE_VOL* regression is significantly positive. It shows that, once we control for various factors, attention stimulates small trades more than large trades, consistent with hypothesis 5a. The conditional gap across small and large trades equals 2.106, which is very large considering that the average unconditional gap equals 0.009.

Comparing the result of the trading volume regressions to those of the return regressions shows that Δ*Other_News* comes out consistently significant with the expected signs. Thus, we provide convincing evidence that the impact of a WSJ article on the immediate market response – in terms of returns and small trades – and on the post-announcement drift is reduced on days with much distracting news. The other variables do not yield such a consistent pattern. This is not surprising given that …

To summarize, the regression analysis shows that the effect of media coverage on abnormal returns is weaker for older firms and on high-news days. Its effect on trading volume is more pronounced for stocks held by more individual investors and for small trades. Moreover, the effect on small trades is weaker for glamour firms and on high-news days. Overall, these results lend support to the attention hypothesis by showing that media coverage has less influence for more visible firms, on high-distraction days and for institutional investors.

5.3 Trading strategies

We find that the post-earnings announcement drift is larger when the announcement is not covered in the media – a result consistent with the attention hypothesis. In order to assess the economic importance of this effect, we study the profitability of a strategy that "sells the drift" when the announcement is covered in the media and "buys the drift" when it is not.

At the end of each month, we assign stocks to surprise quintiles based on their most recent earnings announcements within the last three month using the breakpoints from the previous calendar year. The media portfolio buys firms whose most recent announcement within the past three months was in the top quintile and was covered in the WSJ, and sells short firms whose most recent announcement was in the bottom quintile and was covered in the WSJ. On average, the portfolio includes 27 stocks, of which 14 are bought and 13 sold. The no-media portfolio is formed in a similar fashion, except that it only uses firms whose most recent announcement was not covered in the WSJ. On average, it contains 142 stocks, of which 76 are bought and 66 sold. We estimate monthly portfolio abnormal returns by equally weighting individual stock abnormal returns. Table 9 displays the profitability of each portfolio. The abnormal return – adjusted for size, book-to-market and momentum using the characteristic-based matching procedure in Daniel, Grinblatt, Titman, and Wermers (1997) and Wermers (2004) – on the no media portfolio is 0.97% per month and strongly statistically significant (the t-stat is 5.8). In contrast, the media portfolio yields an abnormal return of 0.17% which is not significantly different from 0 (the t-stat is 0.6). Thus, there is no perceptible post-earnings drift when announcements are covered in the WSJ.

The trading strategy that exploits the drift differential across covered and uncovered announcements is long the no-media portfolio and short the media portfolio. The bottom row of Table 9 shows that it yields an abnormal return of 0.80% per month, significant at the 1% level (the t-stat is 2.7). This is a sizeable risk-adjusted return of 9.6% per annum. We emphasize that our portfolio formation approach is implementable as it only makes use of data that is available on the formation date, and of stocks that are relatively liquid and easy to short – our sample consists mostly of NYSE stocks with at least one analyst.[36] The high profitability of the trading strategy confirms our previous findings that the post-earnings announcement drift is stronger for announcement that are not reported in the WSJ.

Robustness

We also repeated the analysis removing … The results were essentially the same.

[36] D'Avolio (2002), identifying the stocks that are difficult to short, finds that they account for only only 0.6% of the total CRSP market value. They are concentrated in the lowest NYSE size decile and among stocks with a price below $5.

6. Summary and concluding remarks

We study whether inattention causes the post-earnings announcement drift using media coverage as a proxy for investor attention. We compare announcements made by the same firm in the same year and generating the same earnings surprise (as measured by the gap between the median analyst forecast and reported earnings), when one announcement receives more media coverage than the other (as measure by the number of *Wall Street Journal* articles covering the announcement). We find that announcements with more media coverage generate a stronger price and trading volume reaction at the announcement and less subsequent drift. Moreover, this effect is less pronounced for more visible firms (as proxied by age and market-to-book), on high-distraction days (as proxied by the number of firms in the media at the time of the announcement) and for sophisticated investors (as proxied by trade size or the fraction of individual shareholders). Our results lend support to the notion that limited attention is an important source of friction in financial markets.

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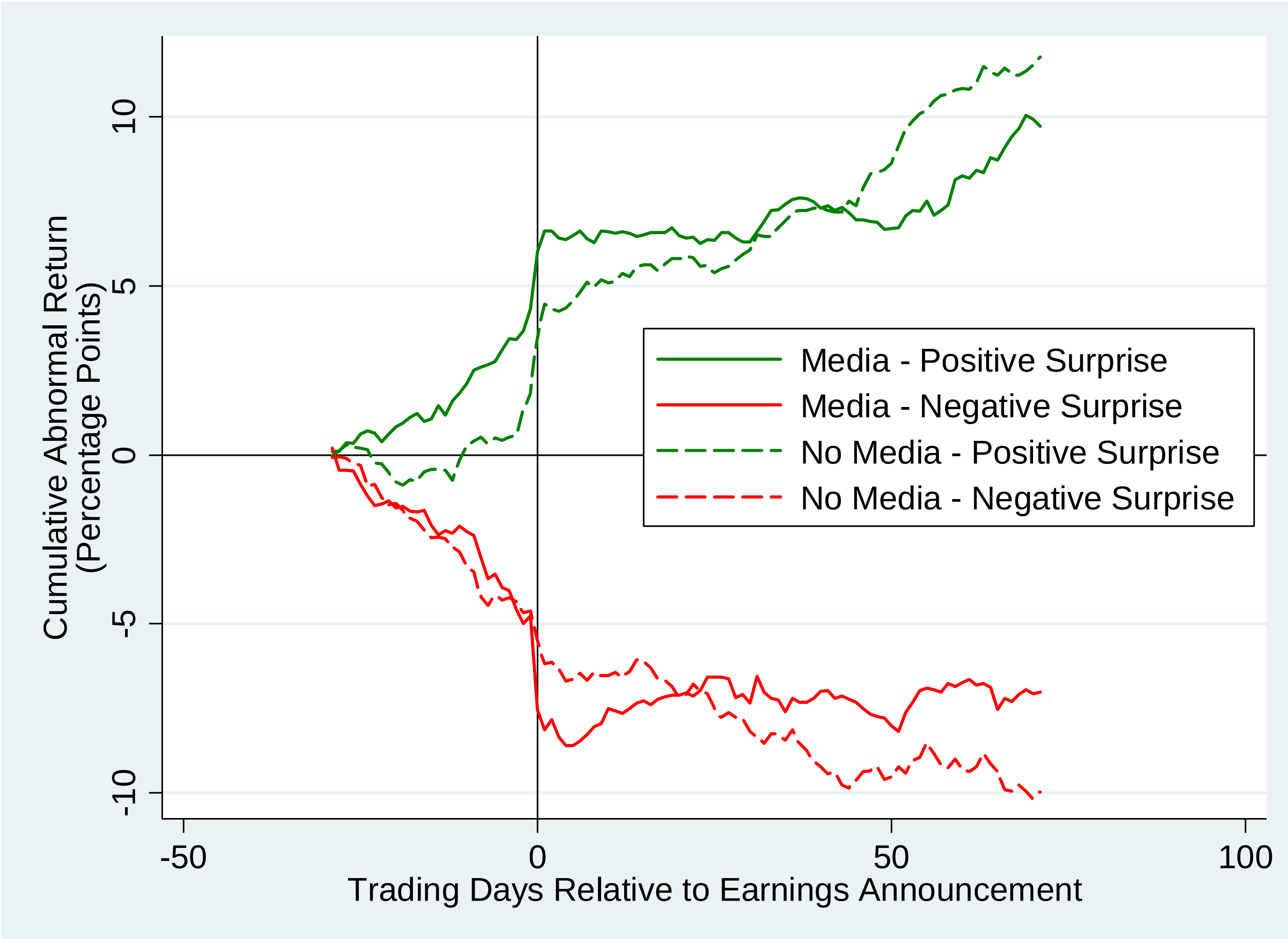

Figure 1

Firms' Valuation around Positive and Negative Earnings Surprises with and without Media Coverage.

Plotted is a firm's cumulative abnormal return from 30 trading days preceding an earnings announcement to 70 trading days following the announcement. The solid curves show the cumulative abnormal return when the announcement is covered in the *Wall Street Journal* on the day of or following the announcement (days 0 or 1), and the dashed curves when it is not covered. Abnormal returns are estimated using the characteristic-based benchmarks of Daniel, Grinblatt, Titman, and Wermers (1997) and Wermers (2004) which control for size, book-to-market and momentum. Positive surprises are those in the top decile of the earnings surprise, *SUR*, and negative surprises are those in the bottom decile (see the text for the definition of *SUR*). The picture uses the sample of matched announcements, i.e. pairs of announcements made by the same firm in the same calendar year and generating the same surprise, with one announcement receiving media coverage while the other does not.

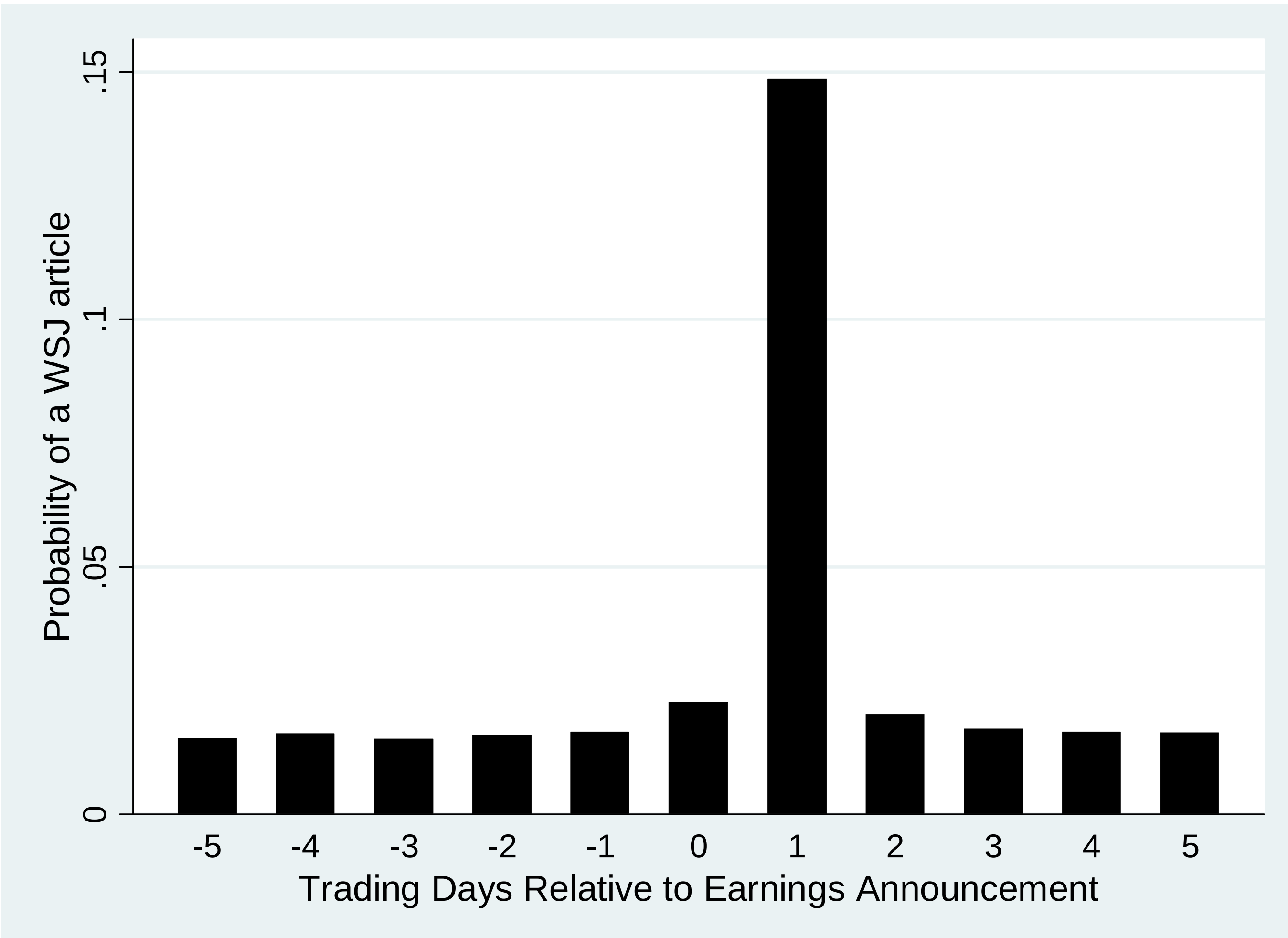

Figure 2

The Probability of a *Wall Street Journal* Article around Earnings Announcements.

The figure displays the fraction of firms featured in the *Wall Street Journal* from 5 trading days preceding an earnings announcement to 5 trading days following the announcement. Day 0 refers to the earnings announcement date.

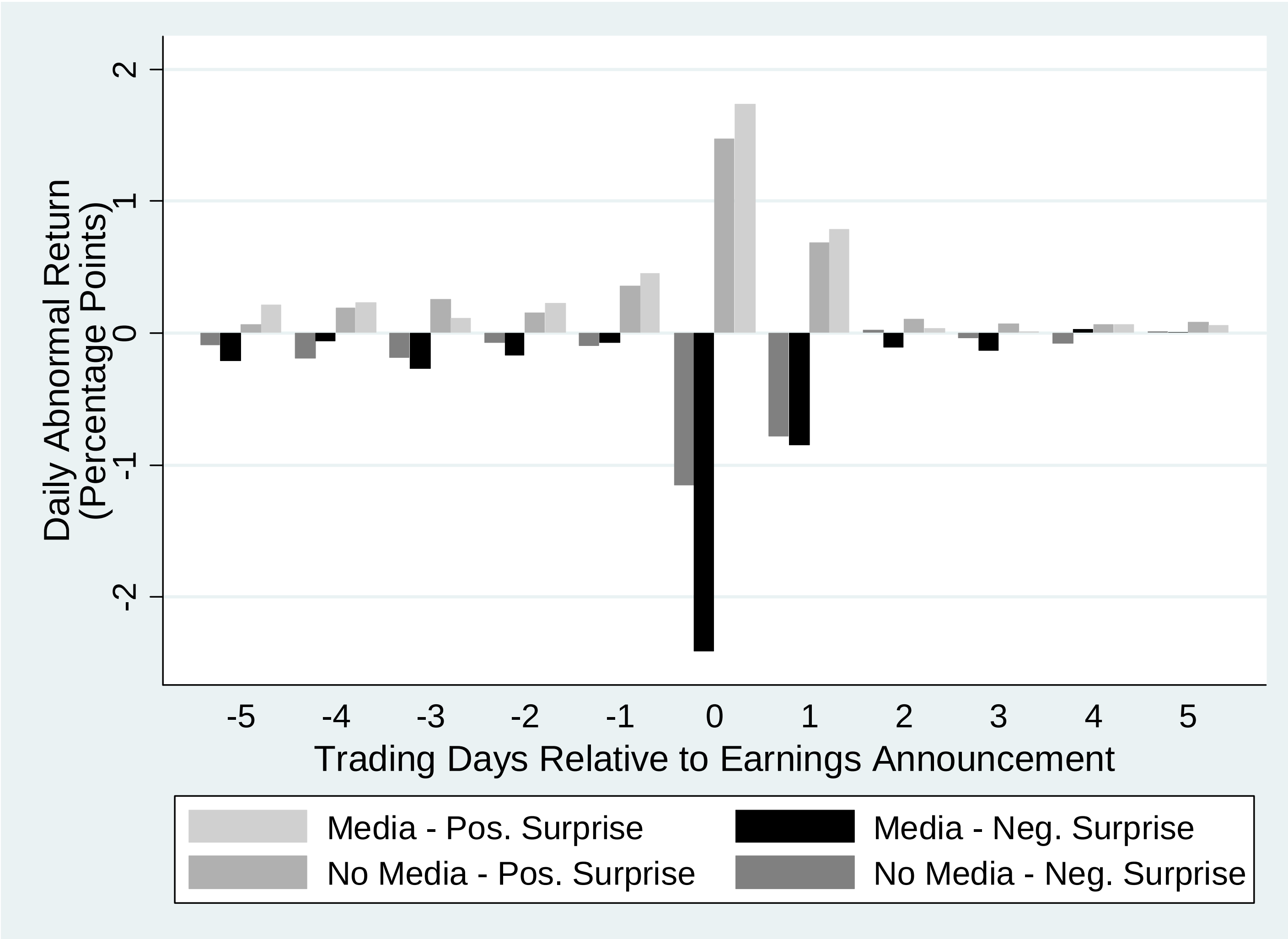

Figure 3

Firms' Daily Abnormal Return around Positive and Negative Earnings Surprises with and without Media Coverage.

The figure displays firms' daily abnormal return from 5 trading days preceding an earnings announcement to 5 trading days following the announcement (day 0 refers to the earnings announcement date). Abnormal returns are estimated using the characteristic-based benchmarks of Daniel, Grinblatt, Titman, and Wermers (1997) and Wermers (2004), which control for size, book-to-market and momentum. Announcements with media coverage are those reported in the WSJ on days 0 or 1. Positive surprises are those in the top decile of the earnings surprise and negative surprises are those in the bottom decile (see the text for the definition of earnings surprise, *SUR*). The picture uses the full sample of (unmatched) announcements.

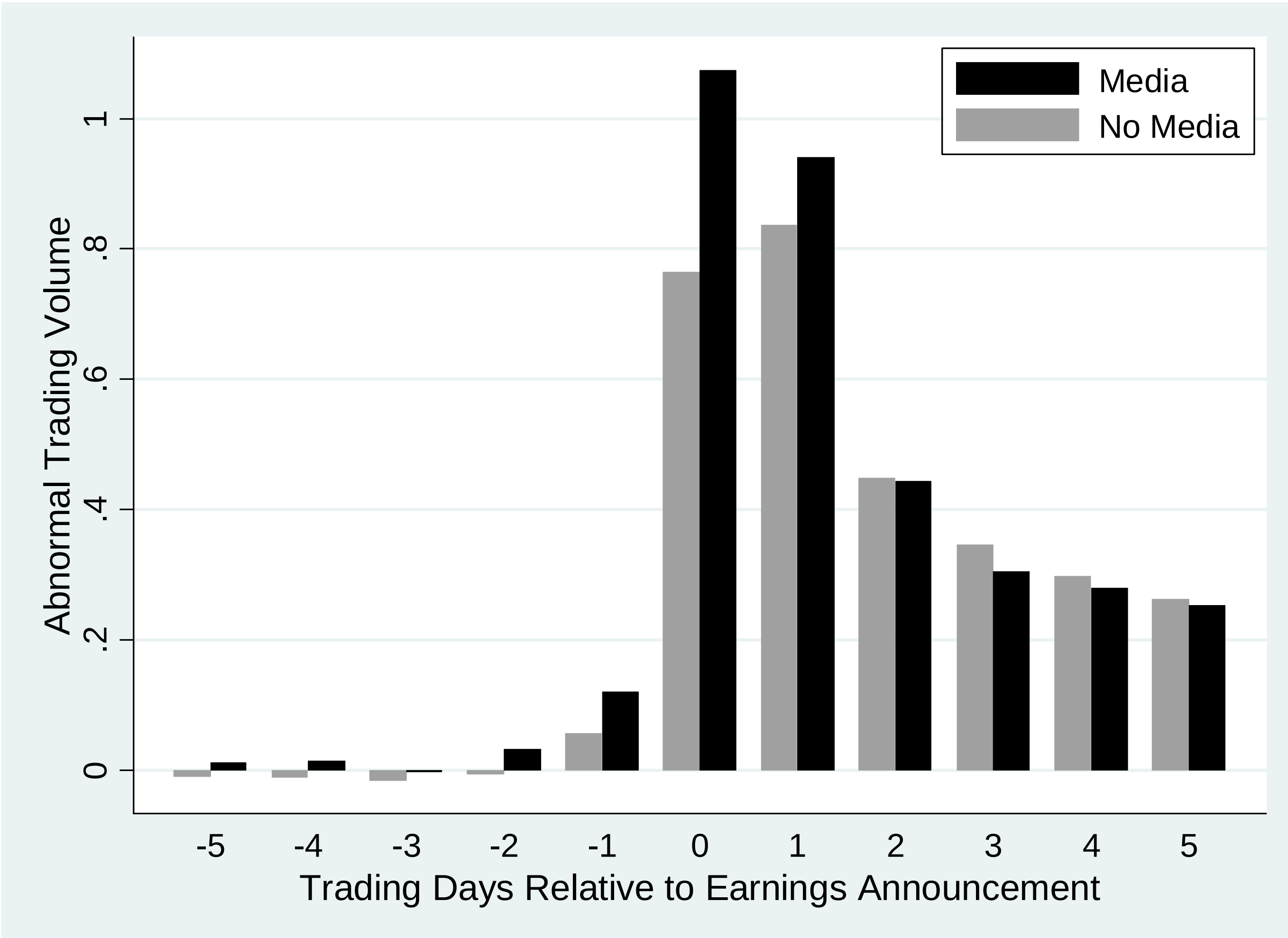

Figure 4

Firms' Abnormal Trading Volume around Extreme Earnings Surprises with and without Media Coverage.

The figure displays firms' daily abnormal trading volume from 5 trading days preceding an earnings announcement to 5 trading days following the announcement (day 0 refers to the earnings announcement date). Abnormal trading volume is defined as the ratio of the difference between the average daily number of shares traded at the announcement (days 0 and 1) and the average daily number of shares traded over the pre-announcement (days -30 to -1), to their sum. Announcements with media coverage are those reported in the WSJ on days 0 or 1. Extreme surprises are those in the top and bottom decile of the earnings surprise (see the text for the definition of earnings surprise, SUR). The picture uses the full sample of (unmatched) announcements.

Table 1

Descriptive Statistics.

Characteristics of announcements and announcing firms. The number of articles is the average number of articles published in the *Wall Street Journal* over the two days that comprise an announcement (the announcement day – day 0, and the day that follows – day 1). Size is measured as the log of the average market capitalization of equity in thousand dollars. Book-to-market is measured as the book-value of equity over market value of equity as of the previous year end. The number of analysts refers to the number of analysts issuing an earnings forecast on the stock. Individual ownership is calculated as one minus the aggregate institutional ownership using 13f data. Amihud (2002)'s illiquidity ratio equals the ratio of a stock's absolute return to its dollar trading volume in a day, averaged over all days in a year. The earnings surprise *SUR* is defined as the difference between the announced earnings and the consensus earnings forecast, normalized by the share price (all split-adjusted).

Panel A: Characteristics of Announcements and Announcing Firms

	Obs.	Mean	Median	S.D.	Min	Max
Log size	54 571	13.943	13.813	1.603	9.185	20.078
Book-to-market	54 049	2.474	1.378	4.022	0.032	133.899
Amihud illiquidity	54 582	0.074	0.007	0.364	0.000	14.980
Individual ownership	54 526	0.547	0.493	0.274	0.001	1.000
Number of analysts	54 582	7.057	5.000	5.623	1.000	42.000
Surprise *SUR*	54 392	-0.006	0.000	0.740	-131.852	0.909
Number of articles	54 582	0.086	0.000	0.202	0.000	1.000

Panel B: Distribution of Announcements by Media Coverage

	Earnings announcements by number of WSJ articles			
	All	No article	1 article on either day 0 or 1	1 article on both days 0 and 1
Number	54 582	45 824	8 163	595
Fraction	100%	84%	15%	1%

Table 2

Market Response to Positive and Negative Earnings Surprises with and without Media Coverage.

Cumulative abnormal returns and abnormal trading volume around earnings announcements for extreme surprise deciles (*SUR*1: bad news, *SUR*10: good news) with and without media coverage are estimated. Announcements with media coverage are those reported in the *Wall Street Journal* on the day of or following the announcement (days 0 or 1). In Panel A, average cumulative abnormal returns are estimated for the 2-day announcement window (*CAR*[0,1]), and for the 70-day post-announcement window (*CAR*[2,71]). Abnormal returns are estimated using the characteristic-based benchmarks of Daniel, Grinblatt, Titman, and Wermers (1997) and Wermers (2004) which control for size, book-to-market and momentum. *t*-statistics are displayed in parenthesis. Panel B shows estimates of abnormal trading volume for the 2-day announcement window. Abnormal trading volume is defined as the difference between the total number of shares traded over the announcement window (days 0 and 1) and the number of shares traded over preceding 30 days (days -30 to -1), divided by their sum. *t*-statistics are displayed in parenthesis.

Panel A: Cumulative Abnormal Returns

	CAR [0,1]			*CAR* [2,71]		
	SUR 1	*SUR* 10	*SUR* 10-*SUR* 1	*SUR* 1	*SUR* 10	*SUR* 10-*SUR* 1
MEDIA 0	-1.90%	2.20%	4.10%	-0.10%	3.80%	3.90%
	(-17.59)	(22.81)	(28.28)	(-0.32)	(11.98)	(8.3)
MEDIA 1	-3.10%	2.50%	5.60%	0.60%	2.30%	1.70%
	(-8.33)	(8.95)	(11.92)	(0.72)	(2.91)	(1.46)
MEDIA 1-*MEDIA* 0	-1.20%	0.30%	1.60%	0.70%	-1.50%	-2.20%
	(-4.08)	(1.24)	(3.9)	(0.79)	(-1.77)	(-1.78)

Panel B: Abnormal Trading Volume

	SUR 1	*SUR* 10	*SUR* 10-*SUR* 1
MEDIA 0	0.118	0.167	0.049
	(21.62)	(33.55)	(6.56)
MEDIA 1	0.219	0.242	0.022
	(18.82)	(25.34)	(1.482)
MEDIA 1-*MEDIA* 0	0.101	0.075	-0.026
	(7.26)	(5.89)	(-1.39)

Table 3

Characteristics of Announcing Firms with and without Media Coverage.

Average characteristics of announcing firms are estimated for earnings in extreme surprise deciles (*SUR*1: bad news, *SUR*10: good news) with and without media coverage. Announcements with media coverage are those reported in the *Wall Street Journal* on the day of or following the announcement (days 0 or 1). Size is measured as the log of the average market capitalization of equity in thousand dollars. Book-to-market is measured as the book-value of equity over market value of equity as of the previous year end. The number of analysts refers to the number of analysts issuing an earnings forecast on the stock. Individual ownership is calculated as one minus the aggregate institutional ownership using 13f data. Amihud (2002)'s illiquidity ratio equals the ratio of a stock's absolute return to its dollar trading volume in a day, averaged over all days in a year. *t*-statistics are displayed in parenthesis.

Log Size

	SUR 1	*SUR* 10
MEDIA 0	12.902	13.052
MEDIA 1	14.452	14.673
MEDIA 1-*MEDIA* 0	1.550	1.621
	(29.85)	(32.06)

Individual Ownership

	SUR 1	*SUR* 10
MEDIA 0	0.620	0.600
MEDIA 1	0.537	0.503
MEDIA 1-*MEDIA* 0	-0.083	-0.097
	(-8.39)	(-9.39)

Book-to-Market

	SUR 1	*SUR* 10
MEDIA 0	3.000	3.229
MEDIA 1	3.211	4.830
MEDIA 1-*MEDIA* 0	0.211	1.600
	(1.36)	(7.75)

Number of Analysts

	SUR 1	*SUR* 10
MEDIA 0	4.314	4.371
MEDIA 1	8.920	9.225
MEDIA 1-*MEDIA* 0	4.606	4.854
	(28.32)	(29.54)

Amihud Illiquidity

	SUR 1	*SUR* 10
MEDIA 0	0.177	0.147
MEDIA 1	0.023	0.015
MEDIA 1-*MEDIA* 0	-0.154	-0.132
	(-7.63)	(-6.19)

Fraction Operating in the Tech Sector

	SUR 1	*SUR* 10
MEDIA 0	0.097	0.110
MEDIA 1	0.210	0.176
MEDIA 1-*MEDIA* 0	0.113	0.066
	(9.42)	(5.25)

Table 4

Descriptive Statistics for Matched Announcements.

Panel A reports the number of announcement pairs for various combinations of media coverage. Each announcement pair consists of a high- and a low-coverage announcement such that they are made by the same firm in the same calendar year, belong to the same surprise decile and one receives more coverage in the *Wall Street Journal* on the day of or following the announcement (days 0 or 1) than the other. High-coverage announcements are featured in the WSJ on day 0 or 1 (so the average daily number of articles is 0.5) or on both day 0 and day 1 (so the average daily number of articles is 1). Low-coverage announcements are featured in the WSJ neither on day 0 nor 1 (so the average daily number of articles is 0) or on either day 0 and day 1 (so the average daily number of articles is 0.5). Panel B presents summary characteristics of firms whose announcements are matched. Size is measured as the log of the average market capitalization of equity in thousand dollars. Book-to-market is measured as the book-value of equity over market value of equity as of the previous year end. The number of analysts refers to the number of analysts issuing an earnings forecast on the stock. Individual ownership is calculated as one minus the aggregate institutional ownership using 13f data. Amihud (2002)'s illiquidity ratio equals the ratio of a stock's absolute return to its dollar trading volume in a day, averaged over all days in a year. Panel C reports the average difference in earnings surprise ΔSUR across matched announcements (high-media minus low-media). The earnings surprise *SUR* is defined as the difference between the announced earnings and the consensus earnings forecast, normalized by the share price (all split-adjusted). *t*-statistics are displayed in parenthesis.

Panel A: Number of Announcements by Media Coverage

		Average daily number of articles about the high-coverage announcement					
		All surprise deciles		*SUR* 1		*SUR* 10	
		0.5	1	0.5	1	0.5	1
Average number of articles about the low-coverage announcement	0	1595	73	199	2	171	5
	0.5	0	184	0	18	0	21
Total number of pairs		1852		219		197	

Table 4 (Continued)

Panel B: Firm Characteristics

	Obs.	Mean	Median	S.D.	Min	Max
Log size	1 852	14.962	14.958	1.552	10.165	19.728
Book-to-makrket	1 828	2.452	1.251	4.457	0.036	96.151
Amihud illiquidity	1 852	0.015	0.001	0.061	0.000	1.076
Individual ownership	1 852	0.503	0.424	0.271	0.016	1.000
Number of analysts	1 852	10.176	9.000	6.277	1.000	37.500
Age	1 852	29.188	25.471	21.755	0.292	76.590

Panel C: Difference in *SUR* across Matched Announcements, ΔSUR

SUR 1	*SUR* 10	*SUR* 10-*SUR* 1
-0.50%	0.00%	0.50%
(-1.12)	(0.1)	(1.06)

Table 5

Impact of Media Coverage on Cumulative Abnormal Returns Around Positive and Negative Earnings Surprises.

The effect of media coverage on average cumulative abnormal returns is estimated over various windows around earnings announcements for extreme surprise deciles (*SUR*1: bad news, *SUR*10: good news). Announcements with media coverage are those reported in the *Wall Street Journal* on the day of or following the announcement (days 0 or 1). Estimates are based on matching sample consisting of pairs of announcements made by the same firm in the same calendar year and belonging to the same surprise decile, with one announcement receiving more media coverage than the other. The difference in average cumulative abnormal returns across matched announcements (high-media minus low-media) is reported for the 2-day announcement window ($\Delta CAR[0,1]$), the 70-day post-announcement window ($\Delta CAR[2,71]$), the 30-day pre-announcement window ($\Delta CAR[-30,-1]$), and the 32-day window covering the pre-announcement and the announcement ($\Delta CAR[-30,1]$). Abnormal returns are estimated using the characteristic-based benchmarks of Daniel, Grinblatt, Titman, and Wermers (1997) and Wermers (2004) which control for size, book-to-market and momentum. *t*-statistics are displayed in parenthesis.

$\Delta CAR[0,1]$				$\Delta CAR[2,71]$			
SUR 1	*SUR* 10	*SUR* 10-*SUR* 1	*SUR* 10+*SUR* 1	*SUR* 1	*SUR* 10	*SUR* 10-*SUR* 1	*SUR* 10+*SUR* 1
-2.40%	-0.40%	2.10%	-2.80%	5.80%	-3.70%	-9.40%	2.10%
(-2.69)	(-0.57)	(1.85)	(-2.48)	(2.59)	(-1.84)	(-3.13)	(0.69)

$\Delta CAR[-30,-1]$				$\Delta CAR[-30,1]$			
SUR 1	*SUR* 10	*SUR* 10-*SUR* 1	*SUR* 10+*SUR* 1	*SUR* 1	*SUR* 10	*SUR* 10-*SUR* 1	*SUR* 10+*SUR* 1
0.20%	2.50%	2.30%	2.10%	-2.20%	2.10%	4.30%	-0.10%
(0.13)	(1.83)	(1.08)	(0.69)	(-1.37)	(1.46)	(1.98)	(-0.04)

Table 6

Differences in Media Coverage across Matched Announcements Around Positive and Negative Earnings Surprises.

The difference in media coverage is estimated around earnings announcements for extreme surprise deciles (*SUR*1: bad news, *SUR*10: good news). Media coverage is measured as the average daily number of articles published about the announcing firm in the *Wall Street Journal*. Estimates are based on matching sample consisting of pairs of announcements made by the same firm in the same calendar year and belonging to the same surprise decile, with one announcement receiving more media coverage than the other. Announcements are matched based on their media coverage the day of or following the announcement (days 0 or 1). The difference across matched announcements (high-media minus low-media) in the average daily number of articles published about the announcing firm in the *Wall Street Journal* is reported for the 2-day announcement window (Δ*MEDIA*[0,1]), the 70-day post-announcement window (Δ*MEDIA*[2,71]), the 30-day pre-announcement window (Δ*MEDIA*[-30,-1]) and the 32-day window covering the pre-announcement and the announcement (Δ*MEDIA*[-30,1]). The matching procedure is designed to produce large Δ*MEDIA*[0,1]. *t*-statistics are displayed in parenthesis.

ΔMEDIA[0,1]		ΔMEDIA[2,71]	
SUR 1	*SUR* 10	*SUR* 1	*SUR* 10
50.50%	51.30%	-0.20%	0.20%
(156.63)	(91.27)	(-0.72)	(0.88)

ΔMEDIA[-30,-1]		ΔMEDIA[-30,1]	
SUR 1	*SUR* 10	*SUR* 1	*SUR* 10
0.40%	1.00%	50.80%	52.30%
(1.19)	(3.33)	(114.38)	(81.57)

Table 7

Impact of Media Coverage on Trading Volume Around Positive and Negative Earnings Surprises.

The effect of media coverage on average trading volume is estimated around earnings announcements over the 2-day announcement window for extreme surprise deciles (*SUR*1: bad news, *SUR*10: good news). Announcements with media coverage are those reported in the *Wall Street Journal* on the day of or following the announcement (days 0 or 1). Estimates are based on matching sample consisting of pairs of announcements made by the same firm in the same calendar year and belonging to the same surprise decile, with one announcement receiving more media coverage than the other. The relative difference in average trading volume across matched announcements is reported for all trades (Δ*VOL*), small trades (Δ*SMALL_VOL*) and large trades (Δ*LARGE_VOL*). The relative volume difference across paired announcements is measured as the difference between the average daily number of shares traded at the announcement (days 0 and 1) for the high- and low-coverage announcements, divided by their sum. Trades are classified by size using a variation of the Lee (1992) firm-specific dollar based trade-size proxy, described in Hvidkjaer (2006). The procedure sorts stocks into quintiles based on NYSE/AMEX firm-size cut-off points and uses the following small- (large-) trade cut-off points within firm-size quintiles: $3,400 ($6.800) for the smallest firms, $4,800 ($9.600), $7,300 ($14.600), $10,300 ($20,600) , and $16,400 (32,800) for the largest firms. *t*-statistics are displayed in parenthesis.

ΔVOL

SUR 1	*SUR* 10	*SUR* 10-*SUR* 1
18.20%	6.90%	-11.30%
(3.07)	(1.3)	(-1.41)

ΔSMALL_VOL

SUR 1	*SUR* 10	*SUR* 10-*SUR* 1
22.30%	1.10%	-21.10%
(4.17)	(0.23)	(-2.88)

ΔLARGE_VOL

SUR 1	*SUR* 10	*SUR* 10-*SUR* 1
15.50%	6.70%	-8.80%
(2.39)	(1.14)	(-0.99)

ΔSMALL_VOL - ΔLARGE_VOL

SUR 1	*SUR* 10	*SUR* 10-*SUR* 1
6.80%	-5.60%	-12.40%
(1.31)	(-0.97)	(-1.6)

Table 8

Determinants of the Impact of Media Coverage on Cumulative Abnormal Returns and Trading Volume Around Positive and Negative Earnings Surprises.

The effect of media coverage on abnormal returns (Panel A) and trading volume (Panel B) is regressed on characteristics of announcements and announcing firms for extreme surprise deciles. In both panels, announcements with media coverage are those reported in the *Wall Street Journal* on the day of or following the announcement (days 0 or 1). Estimates are based on matching sample consisting of pairs of announcements made by the same firm in the same calendar year and belonging to the same surprise decile, with one announcement receiving more media coverage than the other. Regressors are based on the following variables. *Other_News* is the total number of firms mentioned in the WSJ around each earnings announcement (on days 0 and 1) and Δ*Other_News* is the difference in the log of *Other_News* across matched announcements (high-media minus low-media). *Friday* is a dummy variable that equals 1 if the earnings announcement happens on a Friday and 0 otherwise and Δ*Friday* is the difference in the *Friday* dummy across matched announcements (high-media minus low-media).

The market and book values of equity are measured at the end of the previous calendar year. *Size* is the log of the market value of equity. *Age* is the log of the number of years since the firm's first appearance on the CRSP tapes. *Turnover* is defined as the log of the ratio of the number of shares traded during a year to the number of shares outstanding. *Illiquidity* refers to Amihud (2002)'s illiquidity ratio and equals the ratio of a stock's absolute return to its dollar trading volume in a day, averaged over all days in a year. *Individual* is the fraction of individual ownership defined as one minus the fraction of total institutional ownership, obtained by aggregating 13f filings. *Analysts* refers to the number of analysts issuing an earnings forecast on the stock. *Tech* is a dummy that equals 1 if the firms operates in the technology sector and 0 otherwise, according to the classification in Loughran and Ritter (2004).

In Panel A, dependent variable is the difference in average cumulative abnormal returns across matched announcements (high-media minus low-media) is reported for the 2-day announcement window (Δ*CAR*[0,1]) and the 70-day post-announcement window (Δ*CAR*[2,71]).Abnormal returns are estimated using the characteristic-based benchmarks of Daniel, Grinblatt, Titman, and Wermers (1997) and Wermers (2004) which control for size, book-to-market and momentum. *D* is a dummy variable that equals 1 for announcements in the top earnings surprise decile *SUR*10, and 0 for announcements in the bottom decile *SUR*1. The following regressions are estimated:

$$\Delta CAR = a_0 + a_1 D + \sum_{j=1}^{n} b_j (D \times X_j) + \sum_{j=1}^{n} c_j X_j + \sum_{k=1}^{m} d_k C_k + \sum_{k=1}^{m} e_k (D \times C_k),$$

where Δ*CAR* refers to Δ*CAR*[0,1] or Δ*CAR*[2,71], the X_j denote characteristics of announcements (Δ*Other_News* and Δ*Friday*) and of announcing firms (size, age, book-to-market, tech), and the C_k denote control variables (liquidity).

Table 8 (Continued)

In Panel B, the dependent variable is the relative difference in average trading volume across matched announcements for all trades (ΔVOL), small trades ($\Delta SMALL\_VOL$) and large trades ($\Delta LARGE\_VOL$). The relative volume difference across paired announcements is measured as the difference between the average daily number of shares traded at the announcement (days 0 and 1) for the high- and low-coverage announcements, divided by their sum. Trades are classified by size using a variation of the Lee (1992) firm-specific dollar based trade-size proxy, described in Hvidkjaer (2006). The procedure sorts stocks into quintiles based on NYSE/AMEX firm-size cut-off points and uses the following small- (large-) trade cut-off points within firm-size quintiles: \$3,400 (\$6.800) for the smallest firms, \$4,800 (\$9.600), \$7,300 (\$14.600), \$10,300 (\$20,600) , and \$16,400 (32,800) for the largest firms. Regressions of the following type are estimated:

$$\Delta VOL = \alpha_0 + \alpha_1 D + \sum_{j=1}^{n} \beta_j X_j + \sum_{k=1}^{m} \gamma_k C_k ,$$

where the dependent variable is ΔVOL, $\Delta SMALL\_VOL$ or $\Delta LARGE\_VOL$ and the independent variables are defined above for Panel A.

The symbols ***, ** and * denote significance at the 1% and 5% levels respectively, for the two-tailed hypothesis test that the coefficient equals zero. *p*-values based on robust standard errors clustered by firm are displayed in brackets.

Table 8 (Continued)

Panel A: Cumulative Abnormal Returns

	$\Delta CAR\,[0,1]$	$\Delta CAR\,[2,71]$
D x Size	-0.040	-0.168
	[0.186]	[0.124]
D x Age	-0.023*	0.113***
	[0.096]	[0.001]
D x Book-to-market	-0.001	-0.002
	[0.628]	[0.806]
D x Analysts	0.012	0.036
	[0.468]	[0.475]
D x Tech	0.009	-0.050
	[0.752]	[0.603]
D x Individual	0.007	0.051
	[0.852]	[0.606]
D x ΔOther_News	-0.088*	0.223*
	[0.081]	[0.092]
D x ΔFriday	0.023	0.053
	[0.419]	[0.527]
D x Turnover	-0.020	-0.087
	[0.521]	[0.346]
D x Illiquidity	-0.031	-0.093
	[0.234]	[0.299]
D	0.488	1.479
	[0.149]	[0.217]
Size	0.014	0.064
	[0.509]	[0.337]
Age	0.017	-0.064**
	[0.115]	[0.017]
Book-to-market	0.002	0.005
	[0.405]	[0.493]
Analysts	-0.006	-0.065*
	[0.591]	[0.096]
Tech	0.000	0.014
	[0.983]	[0.825]
Individual	-0.022	-0.041
	[0.462]	[0.572]
ΔOther_News	0.062	-0.180*
	[0.103]	[0.087]
ΔFriday	-0.002	-0.018
	[0.909]	[0.756]
Turnover	-0.011	0.041
	[0.625]	[0.425]
Illiquidity	0.010	0.017
	[0.589]	[0.754]
Intercept	-0.182	-0.509
	[0.452]	[0.500]
R Squared	0.060	0.090
Observations	411	411

Table 8 (Continued)

Panel B: Trading Volume

	ΔVOL	*ΔSMALL_VOL*	*ΔLARGE_VOL*	*ΔSMALL_VOL - ΔLARGE_VOL*
D	-0.137	-0.220***	-0.120	-0.100
	[0.103]	[0.005]	[0.190]	[0.200]
Size	0.186	0.092	0.225*	-0.133
	[0.124]	[0.417]	[0.083]	[0.252]
Age	-0.012	0.014	-0.008	0.022
	[0.808]	[0.766]	[0.880]	[0.602]
Book-to-market	0.004	0.007	0.003	0.004
	[0.506]	[0.101]	[0.615]	[0.278]
Analysts	0.069	0.003	0.077	-0.073
	[0.267]	[0.956]	[0.250]	[0.268]
Tech	0.027	0.100	0.005	0.095
	[0.815]	[0.346]	[0.969]	[0.397]
Individual	0.278*	0.047	0.327*	-0.280*
	[0.089]	[0.752]	[0.069]	[0.073]
ΔOther_News	-0.104	-0.473***	-0.102	-0.371**
	[0.627]	[0.007]	[0.670]	[0.047]
ΔFriday	-0.047	-0.122	-0.076	-0.046
	[0.715]	[0.272]	[0.581]	[0.648]
Turnover	0.238**	0.041	0.300***	-0.259***
	[0.024]	[0.686]	[0.007]	[0.002]
Illiquidity	0.146	0.097	0.170	-0.073
	[0.156]	[0.304]	[0.121]	[0.443]
Intercept	-2.249*	-0.718	-2.824*	2.106*
	[0.098]	[0.575]	[0.052]	[0.099]
R Squared	0.040	0.050	0.050	0.080
Observations	400	400	400	400

Table 9

Performance of Post-Earnings Announcement Drift Portfolios.

The monthly abnormal return of a trading strategy that exploits the drift differential across covered and uncovered announcements from March 1993 to December 2002 is estimated. At the end of each month, we assign stocks to surprise quintiles based on their most recent earnings announcements within the last three month and the breakpoints from the previous calendar year. The media portfolio buys firms whose most recent announcement within the past three months was in the top quintile and was covered in the WSJ, and sells short firms whose most recent announcement was in the bottom quintile and was covered in the WSJ. The no-media portfolio is formed in a similar fashion, except that it only uses firms whose most recent announcement was not covered in the WSJ. The last row reports the abnormal return of a trading strategy that is long the no-media portfolio and short the media portfolio. Abnormal returns are estimated using the characteristic-based benchmarks of Daniel, Grinblatt, Titman, and Wermers (1997) and Wermers (2004) which control for size, book-to-market and momentum. *t*-statistics are displayed in parenthesis.

Portfolio	Monthly Abnormal Return
No-media	0.97%
	(5.85)
Media	0.17%
	(0.55)
Trading strategy: Long No-media and short Media	0.80%
	(2.68)