Herding in analysts' recommendations: The role of media*

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Abstract

This study investigates the impact of media on analysts' herding behavior when making stock recommendations. We find three main results. First, for firms with high news coverage, price reactions following analysts' recommendation revisions that are away from the consensus are weaker than to those closer to it, indicating that the market recognizes analysts' tendency to issue bold recommendations when the firm is intensively covered in the spotlight. Second, when the firm has negative media sentiment, markets react strongly to recommendation revisions that are away from the consensus – consistent with the notion that the market believes that analysts have an incentive to herd following negative news sentiment. Third, disagreement in the media is associated with higher tendency to herd among analysts. These findings are robust to the confounding effect of news flows on returns as well as to alternative explanations. Our study offers new insights into the understanding of analysts' herding behavior.

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1 Introduction

"Collective fear stimulates herd instinct, and tends to produce ferocity toward those who are not regarded as members of the herd." – B. Russell

Security analysts tend to herd by issuing recommendation revisions that are closer to the consensus (Welch (2000) and Jegadeesh and Kim (2010)). Using a comprehensive news dataset from Reuters, the purpose of this study is to address the following questions: whether the media has an impact on the herding behavior of analysts when making stock recommendations and, if so, what types of analysts are more influenced by the media? We specifically examine three prominent features of media namely, news coverage, news sentiment, and media disagreement.[1]

News coverage (defined as the number of news articles covering the firm's stock over the quarter prior to the analyst' recommendation revision) can affect the herding tendency of analysts via two competing hypotheses. First, since public news can reduce information asymmetry in the market (Tetlock, 2010), high news coverage may narrow the information gap among security analysts as some private information of informed analysts becomes public. The information hypothesis posits that, because analysts' information is correlated, they issue similar recommendations. This hypothesis therefore predicts a positive association between news coverage and analysts' "herding".[2] The second competing hypothesis is the incentive hypothesis, which says that, when the stock attracts high attention from the market, analysts' recommendations are more likely to be covered in the media.[3] The analyst thus has a stronger incentive to issue bold recommendations that are away from the consensus

[1]Section 2 provides a formal discussion of our hypotheses and a brief review of studies on the impact of news on stock returns.

[2]According to the information hypothesis, analysts are not herding. Rather, they take similar actions because they have access to similar information set.

[3]Barber and Odean (2008) use news coverage as a proxy for market's attention on the stock.

to gain the attention of the media. Consequently, the incentive hypothesis predicts a negative association of news coverage on analysts' tendency to herd.

We employ the model of Jegadeesh and Kim (2010) to detect herding among analysts based on the market's reaction to recommendation revisions. Jegadeesh and Kim (2010) show that in an efficient market, if the analyst has an incentive to herd, the market's reaction to analyst's recommendation revisions that are away from the consensus will be stronger than to those closer to it. When the stock is intensively covered in the media, we find that market's reaction to recommendation revisions that are away from the consensus is significantly weaker than to those that are closer to it. This finding suggests that the market recognizes that analysts have a lower tendency to herd following high media coverage of the stock – consistent with the prediction of incentive hypothesis.

We next examine the impact of news sentiment on analysts' herding tendency. Since news sentiment can affect the market's opinion about the stock (Tetlock, 2007), we conjecture that it also has an impact on the tendency to herd among analysts. The impact of negative news sentiment could be different from that of positive sentiment. Analysts are generally reluctant to convey negative information to the market because it would potentially hurt their business relationships with the company. This reluctance is somewhat relieved during negative news sentiment because their negative view is consistent with the consensus opinion of the market about the stock. Consequently, analysts tend to herd more following times of negative news sentiment. Employing the quantitative news tone score from Thomson Reuters, we compute the news sentiment score for a stock as the average of news tone scores of all news articles related to the stock over the past quarter prior to the recommendation revision date. Following times of negative news sentiment, we find that markets react much more strongly to recommendation revisions that are away from the consensus than to those closer to it. This finding is consistent with the notion that the market recognizes analysts' stronger tendency to herd when the firm's news sentiment is negative.

The last feature of news that we examine is media disagreement about the firm's stock. When media disagreement is strong, the market is uncertain about the future prospect of the firm (Dzielinski and Hasseltoft, 2014). Investors thus tend to seek the opinion of analysts when making stock selections. Because the increasing importance of the analyst's recommendation makes it more costly for her to be "wrong", she has a stronger incentive to herd during those times. Motivated by Dzielinski and Hasseltoft (2014), we proxy for media disagreement by news dispersion, defined as the standard deviation of news tone scores of all articles related to the company's stock. Dzielinski and Hasseltoft (2014) show that this news dispersion measure is a good proxy for investor disagreement. By allowing analysts' tendency to herd to be conditional on media disagreement, we find results that are consistent with the above prediction: market's reactions to recommendations revisions that are away from the consensus are stronger than to those that are closer to it. This result suggests that the market is more aware of analysts' stronger tendency to herd when the media disagreement is higher.

Having documented the impact of news on the herding tendency among analysts, the second goal of our study is to examine which types of analysts are more influenced by the media. Motivated by the literature (for example, Chen and Jiang (2006)), we examine three primary characteristics of analysts: experience, investment banking affiliation, and analysts covering stocks with high trading volume. The incentive hypothesis posits that, because experienced analysts are more concerned about maintaining their reputation and since they are more reluctant to issue negative information, they have more incentives to herd than other analysts following negative news sentiment.[4] Investment banking affiliation can represent another incentive to herd. Since analysts whose brokerage firm has an advisory relationship with the company's stock have an interest in maintaining the market's optimistic view of the stock, the incentive hypothesis predicts that they are less likely to herd following negative news sentiment. Similarly, the incentive hypothesis also predicts that analysts who cover stocks with high trading volume (which are typically associated with high trading commissions as argued by Chen and Jiang (2006)) are less likely to herd following negative news sentiment. Our regression results are consistent with all three predictions. We find that experienced analysts are more likely to herd following times of negative news sentiment. Affiliated analysts and those covering high trading volume stocks are, however, less likely to herd when the news sentiment is negative.[5]

This study contributes to the literature on news analytics in accounting and finance as well as the literature on analysts' herding. Even though news has been shown to affect future stock returns, to the best of our knowledge we are not aware of a published study that examines how news affects the herding behavior of analysts, whose stock recommendations can be "influential" in the market (Loh and Stulz, 2011). Rees, Sharp and Twedt (2015) is perhaps the closest study to ours, though their study, which is not about herding among analysts, focuses on comparing the characteristics of analysts who were featured in the media versus those who were not. In both analyst herding literature and the literature on news analytics in accounting and finance, our study is one of the first to simultaneously examine three prominent

[4]An alternative hypothesis is that experienced analysts, who have been in the job for a long time, are more likely to be overconfident than inexperienced analysts. Thus, since overconfident analysts tend to overweight their private information, they do not herd toward the consensus in their recommendations. Another hypothesis is that experienced analysts are more likely to have skills and more private information;. They therefore do not herd based on public information. The prediction of these two hypotheses are in contrast to the incentive hypothesis.

[5]Section 5.2 discusses alternative explanations including the potential influence of analysts on news sentiment.

features of news flows on analysts' herding tendency. Investigating the effects of all news characteristics simultaneously is important because the intensity of news coverage and the strength of media disagreement can affect an analyst's interpretation of the current news sentiment. This joint examination also allows us to find out whether the effect of news sentiment is subsumed once we control for the other news features; thereby providing the literature with a more complete picture on the role of the media in affecting analysts' incentives to herd. We further contribute by examining the types of analysts that are more influenced by the media when making stock recommendation revisions. Finally, we employ a large sample of firm-specific news with over 1.6 million news articles between 2003 and 2012. This compares favorably with 2,024 articles in Rees et al. (2015) and other prior studies on news analytics in accounting and finance. Tetlock et al. (2008) argue that one should examine all types of news by using as large a sample of news as possible because it limits the scope for "dredging for anomalies" – a phrase that they quote from Fama (1998) to mean searching through particular news events in order to find "significant" results.

The next section formally develops the hypotheses for this study. Our study relies on the comprehensive news data from Thomson Reuters, which is described in Section 3. Section 4 outlines the methodology of Jegadeesh and Kim (2010) to detect the herding behavior of analysts. Section 5 reports results for the impact of media on analysts' herding behavior – the first goal of our study. Section 6 examines which types of analysts are more influenced by the media – our second goal. We conclude in Section 7.

2 Related literature and hypothesis development

2.1 The role of news in the financial market

Since news is an important source of information for the market, researchers and practitioners have long been interested in how news and the media affect stock prices and the behavior of all market participants. With the help of modern news analytics technology such as that of Thomson Reuters, it is therefore not surprising that research in this area has recently received considerable attention. Fang and Peress (2009), for example, examine the monthly cross-sectional relationship between media coverage and stock returns and find that stocks not covered by the media earn 3% per year more than those that are covered by the media. Antweiler and Frank (2006) conduct event studies using corporate news stories from the Wall St Journal (WSJ) and document short-run reversals after the news publication. Tetlock (2007) analyzes negative words (as defined by the Harvard IV4 Dictionary) in the WSJ *Abreast of the Market* and finds that negative words in the column predict negative future stock returns. Similarly, Tetlock et al. (2008) show that negative words from the Dow Jones News Service (DJNS) and the WSJ can predict earnings and returns on the S&P500 firms. Employing a similar news analytics technique to Tetlock (2007), Engelberg (2008) counts the number of negative words in the firm's earnings announcement and finds that the qualitative information in the text has stronger return predictability than quantitative financial measures such as Standardized Unexpected Earnings. Besides news sentiment, the literature has also examined the effect of other news characteristics on stock returns. Tetlock (2011) investigates the similarity of words between news articles and shows that investors actually overreact to stale news in the short run. Dzielinski and Hasseltoft (2014) find that news dispersion, measured as the standard deviation of the quantitative tone score of all news articles in Thomson Reuters News

Analytics database, can predict negative future returns, and more importantly is a better measure of investor disagreement than analyst forecast dispersion.

Although the impact of news on stock returns is well-documented, its impact on the behavior of market experts such as security analysts, whose recommendations can be influential in the market (Loh and Stulz, 2011), is still not known. Our study contributes to the growing literature of public news releases by showing that news coverage, news sentiment, and media disagreement about the company's stock can jointly affect analysts' herding behavior. We also contribute to the literature on analysts' herding by showing that the impact of the media on herding is conditional on the characteristics of analysts.

2.2 The impact of news on the incentive to herd among security analysts

Our study has two goals. The first goal is to examine the impact of the media on the herding behavior of analysts. The second goal is to examine which types of analysts are more influenced by the media. For the first objective, we investigate three main features of news that are likely to affect analysts' analysis, namely news coverage (defined as the number of news articles covering the company's stock over the past quarter), news sentiment (defined as the general tone of the media about the stock), and media disagreement (defined as the dispersion of news tone in the media).

Prior research (for example, Tetlock (2010) and Bushee et al. (2010)) has shown that news coverage can reduce information asymmetry in the market. High news coverage thus narrows the information gap among analysts as some private information of analysts has been revealed to the public. The information hypothesis posits that, since analysts have access to similar information, they issue similar recommendations.

This hypothesis therefore predicts a positive relationship between news coverage and the similarity in stock recommendations of analysts.

On the contrary, the incentive hypothesis posits that, intensive news coverage also indicates that the company's stock has attracted high attention from the media and the market. Rees et al. (2015) show that being covered in the media significantly benefits the analyst' careers. Thus, during times of high news coverage, analysts are more willing to issue bold recommendations that are away from the consensus so that their opinion could gain the media's attention. But even when the chance that the analyst's recommendation revision is covered in the media is very low in the midst of intensive news coverage, it is still less costly for the analyst to be wrong because her recommendation revision does not attract as much attention as that during the low coverage period. As a result, she still has a higher incentive to issue a bold recommendation revision. Indeed, Barron et al. (2002) find that the consensus among analysts' forecasts decreases after an earnings announcement, suggesting that they put more weight on their private information when producing reports after the news. The incentive hypothesis predicts that analysts' incentive to herd is lower when media coverage is high.

Hypothesis on news coverage (H1a): *if analysts herd when making stock recommendations, the incentive to herd is reduced when the firm is intensively covered in the media.*

Alternative hypothesis of news coverage (H1b): *the tendency to issue recommendation revisions toward the consensus is higher when the firm is intensively covered in the media.*

Since news sentiment affects the market's opinion about the stock as shown in Tetlock (2007) and others, in this study we hypothesize that it may also have an influence on analysts' recommendation revisions. In fact, Rogers and Grant (1997) analyze 187 sell-side analysts' reports between 1993 and 1994 and find that about half of them uses on information not contained in the annual report. This finding suggests that analysts also rely on other external sources of information when producing recommendations. In this article, we point out that public news content, specifically the tone of the news coverage, is one of them. The impact of news sentiment on stock prices is, however, different for pessimism and optimism. Tetlock (2007) finds that media pessimism is a stronger predictor of future stock returns than optimism. Thus, we expect that negative news sentiment could affect analysts' recommendation revisions more than does the positive sentiment. Furthermore, since analysts tend to herd more for downgrades (Jegadeesh and Kim (2010) and others), we conjecture that analysts are even more reluctant to deviate away from the consensus when the firm has had negative news sentiment. This line of argument is similar in spirit to the incentive hypothesis: during negative sentiment period, exaggerating differences from the consensus (for example, by upgrading the recommendation while the consensus is downgrading) would make the analyst's revision more noticeable, and hence it would be more costly for her reputation and career if her recommendation later turns out to be "wrong". By herding toward the consensus, her reputation is less likely to be damaged because, after all, she is not the only "wrong" in the crowd. In fact, Hong et al. (2000) find that being bold and wrong would hurt the analyst's career outcomes while being bold and correct does not significantly improve her career prospects. Another mechanism that is also in line with the incentive hypothesis is that analysts are reluctant to convey negative information to the market because it would hurt their business relationships with the company. This reluctance, however, could be relieved when the news sentiment is also negative because the analyst is not alone in issuing pessimistic recommendation. Indeed, Conrad et al. (2006) show that if there are enough analysts issuing negative opinion on the stock, this may relieve the analyst from her conflict of interests with the firm. As a result, she is more likely to herd following times of pessimism in the media. For news sentiment, the predictions of the incentive hypothesis and the information hypothesis are similar. The information hypothesis says that analysts issue similar stock recommendations following negative news sentiment because negative news is more informative than positive news. Similar to Welch (2000), without observing the real intention of analysts when making recommendations, we cannot differentiate the two hypotheses. Although it is not the goal of our study to test these two competing hypotheses, the findings from Hypothesis 1 can suggest which hypothesis is supported. Since Jegadeesh and Kim (2010) find that analysts have an incentive to herd when making stock recommendations, we state our second hypothesis as follows:

Hypothesis on news sentiment (H2): *analysts have a stronger incentive to herd following negative news sentiment of the firm.*

When media disagreement is high and investors are uncertain about the future prospect of the firm, they tend to seek the opinion of analysts. Again, the increasing importance of the analyst's recommendation makes it more costly for her to be "wrong". Consequently, analysts have more incentives to herd when media disagreement is strong. Motivated by Dzielinski and Hasseltoft (2014), we proxy for disagreement by news dispersion, which is the standard deviation of news sentiment scores of all news articles related to the firm obtained from Thomson Reuters. Dzielinski and Hasseltoft (2014) show that, compared with analysts' forecast dispersion, news dispersion is a better proxy for disagreement and a stronger predictor of future stock returns. The alternative hypothesis is that disagreement among investors as well as analysts could be reflected in the media, and hence cause the news dispersion to be high. Since analysts now disagree about the future prospect of the firm, we should observe less herding behavior of analysts. We therefore have the following hypotheses:

Hypothesis on news dispersion (H3a): *the incentive to herd among analysts increases when disagreement in the media is strong.*

Alternative hypothesis on news dispersion (H3b): *the tendency to herd among analysts decreases when disagreement in the media is strong.*

Previous research has shown that analysts are a heterogenous group in which their herding behavior is conditional on their characteristics and incentive structures. In order to examine which type of analysts are more influenced by the media, we look at three characteristics of analysts, namely experience, investment banking affiliation, and those covering stocks with high trading volume. Our objective is to examine how these characteristics affect analysts' herding behavior following negative news sentiment, which is the most important feature of the media.

The first analysts' attribute is experience. According to the incentive hypothesis, experienced analysts are more likely to herd than young analysts because being wrong is more costly to their reputation that they have been building for years. Since times with pessimistic media sentiment are particular sensitive, experienced analysts are more likely to herd following the negative news sentiment of the firm. Another reason for experienced analysts to herd more during negative news sentiment periods is because of the pressure from their connections with the company. Experienced analysts tend to have established connections and career interests with the company that they cover. In normal times, this connection prevents them from downgrading their stock recommendations. During times of negative news sentiment, since both the media and the market agree that the company's future prospects are dim, experienced analysts are relieved from the pressure and more free to follow the consensus. This line of argument is, again, consistent with the incentive hypothesis.[6]

An alternative hypothesis is the overconfidence hypothesis, which posits that overconfident analysts overestimate the precision of their private signal about the company's stock, and therefore should not be affected by public media sentiment. This overconfidence hypothesis arises from biased self-attribution in which analysts do not know their true ability and are more confident about his own private information and analysis but not about public information (Daniel et al., 1998; and Gervais and Odean, 2001). Since experienced analysts are more likely to be overconfident in their job over time than inexperienced analysts, the overconfidence hypothesis predicts no relation between media sentiment and the herding behavior of experienced analysts. Another alternative hypothesis is that experienced analysts are more likely to be skilled in their job and gaining more solid networks, which, in turn, give them more private information.[7] Those experienced analysts, therefore, tend to overweight their private information and underweight public information. Thus, this hypothesis, which we call ability hypothesis, has a similar prediction to the overconfidence hypothesis.

The second attribute is analysts' investment banking affiliation. Analysts, whose brokerage firm has an advisory relationship with the company, are rewarded for op-

[6]The literature offers mixed predictions on the relation between experience and analysts' herding tendency. The model of Scharfstein and Stein (1990) predicts that young and inexperienced analysts tend to herd more whereas, in the model of Prendergast and Stole (1996), those analysts are more likely to issue bold recommendations in order to make their names stand out from the crowd.

[7]Prior research (for example, Stickel (1992), Mikhail et al. (1999), and Hong et al. (2000)) has shown that analysts with higher ability are more likely to stay longer in the profession.

timistic recommendations, which help generate underwriting businesses and trading commissions (Hong and Kubik, 2003). Since negative news sentiment is typically associated with pessimistic consensus, the incentive hypothesis predicts that affiliated analysts are less likely to herd following negative news sentiment. Finally, we follow Chen and Jiang (2006) to employ high trading volume as a proxy for stocks with potentially high commissions. The incentive hypothesis predicts that, analysts covering those stocks earn their commissions from generating interests in the stock, they are less likely to downgrade their stock recommendations, which are more likely during pessimistic periods. Accordingly, we hypothesize that those analysts have lower incentive to herd following negative media sentiment.

Hypothesis on analysts' characteristics and herding (H4): *analysts with different characteristics have different incentives to herd following negative news sentiment.*

There is no obvious reason to expect that analysts with those attributes would have an opposite herding incentive to the other analysts following times of high news coverage and media disagreement. If anything, the incentive hypothesis predicts that those analysts would have a stronger incentive to herd during times of strong media disagreement and low news coverage. For example, when the firm has already had intensive news coverage, the recommendation revision of analysts with an investment banking affiliation does not attract any more attention than that of non-affiliated analysts. Since affiliated analysts are now more free, they are even more likely to issue bold recommendations that are away from the consensus. As a result, we hypothesize that affiliated analysts are less likely to herd than other analysts following intensive news coverage of the firm. The impact of media disagreement goes in the other direction. When the media disagreement about the firm is strong and investors are uncertain about the future of the firm, they tend to seek the opinion of affiliated analysts for a stock recommendation, with the belief that those analysts are more likely to possess private information. This makes it more costly for affiliated analysts to issue bold recommendations that stand out of the crowd. As a consequence, affiliated analysts are more likely to issue recommendations that are closer to the consensus following times of strong media disagreement.

3 Data

Our study takes advantage of the modern news analytics technology of Thomson Reuters News Analytics (TRNA), which is available for the period between January 2003 and December 2012. Hendershott et al. (2015) and Sinha (2012) employ this news database to study the informativeness of institutional trading and market's reaction to news.[8] Thomson Reuters collects and analyzes firm-level news from major news sources such as Dow Jones Newswires, the Wall St Journal, Reuters, and other regional newspapers. Specifically, Thomson Reuters quantifies the tone of each relevant news item using a proprietary algorithm and provides sentiment scores that we use in this study. For each news article, we compute its sentiment score as follows:

$$NewsTone = positive - negative \tag{1}$$

where *positive* and *negative* are respectively the probabilities of the news being positive and negative as calculated by Thomson Reuters. (Thus, $positive + neutral + negative = 1$). These sentiment scores are computed based on a hybrid system of

[8]See Hendershott et al. (2015) and Heston and Sinha (2014) for a description of the advantages of TRNA over other conventional methods of quantifying news tone. The white paper outlining Thomson Reuters's methodology is available upon request.

textual analysis methods including lexical analysis, linguistic parsing, and machine learning together with experts' annotation of words.[9] Thomson Reuters also provides us with the relevance score of the news item, which measures how relevant the news item is to firm i. Intuitively, it is calculated by comparing the relative number of occurrences of the firm with the number of occurrences of other firms within the text of the news item. If the firm is mentioned in the headline, then the news item is 100% relevant to the firm (relevance score = 1). For stories that mention multiple firms, the firm with the most mentions will have the highest relevance score. Thomson Reuters's white paper says that the relevance score allows the distinction between the three cases: (1) when the relevance score is close to one, the company is "one of the determinant players" in the article; (2) when the relevance score is between 0.8 and 0.2, the firm is "one of several mentioned substantively in the article"; and (3) when the relevance score is less than 0.2, the company is a "minor player" in the article. To ensure that the news item is highly relevant to the firm, we require that the relevance score to be greater than 0.8. Our results are robust to using news items with 100% relevance scores.[10]

We then compute the average tone (or sentiment) score of the media coverage for stock i (denoted by $tone_{i,t}$) as the average of all $NewsTone$'s over the past quarter. We also calculate news tone dispersion for the stock, $StdTone_{i,t}$, as the standard deviation of $NewsTone$ over the past quarter.[11] We call this measure "media disagreement", which Dzielinski and Hasseltoft (2014) show to be good proxy for investor

[9]For the human annotation process, Thomson Reuters's white paper says that each word is annotated by three experts "who are working from a carefully prepared script." The words are presented to each annotator in a random order and the consensus taken as the final word score.

[10]Some large news items with lengthy body text are received by TRNA in parts. We only include the final take of the complete news in which Thomson Reuters provides the quantitative news scores for the whole article. By doing this, we avoid double counting large news items.

[11]In unreported robustness tests, we also compute all the news measures over the past month and our results do not qualitatively change.

disagreement. Henceforth, we use the terms "media disagreement" and "news dispersion" interchangeably.

We obtain stock recommendations from IBES. We use IBES's stopped recommendation file to remove revisions that are made after stopped dates. We employ daily returns for all stocks with share codes of 10 and 11 (excluding closed-end funds, Real Estate Investment Trusts, trusts, American Depository Receipts, and foreign stocks) from the Center for Research in Security Prices (CRSP) and accounting information from Compustat. IBES standardizes analyst recommendations ("strong buy", "buy", "hold", "sell", and "strong sell") and converts them to numerical scores where "1" is strong buy, "2" is buy, and so on. For the ease of interpretation, we reverse IBES's recommendation scores so that "1" corresponds to a strong sell and "5" corresponds to a strong buy. Following Jegadeesh and Kim (2010), stocks must also satisfy the following criteria: (1) there should be at least one analyst who issues a recommendation for the stock and revises the recommendation within 180 calendar days; (2) at least two analysts, other than the revising analyst, should have active recommendations for the stock as of the day before the revision. A recommendation is considered active for up to 180 days after it is issued or until the IBES stopped file records that the analyst has stopped issuing recommendations for that stock; and (3) the firm should be covered in CRSP as well as TRNA.

Table 7 reports summary statistics for our U.S. sample between 2003 and 2012. After merging data across various databases, there are a total of 5,098 unique firms in our sample. The sample starts with 3,876 firms in 2003 and, by 2012, the number decreases to 3,066 firms. The total number of analysts issuing revisions of stock recommendations is 5,359. The number of analysts vary year by year ranging from 1,391 analysts to over 2,000 analysts. The drops in number of analysts and firms coincide with the period of financial crisis when many analysts stopped issuing recommendations for firms that ceased to exist. Consistent with Barber et al. (2001), analysts are reluctant issue stock recommendations of “strong sell” (average about 4% of the recommendations between 2003 and 2012 and less than 8% in any given year) or “sell” (average about 8% over the whole sample period and less than 10% in any given year). The proportions of “buy” and ”strong buy” recommendations are much higher with averages of 24.42% and 18.32% of the total recommendations, respectively, indicating analysts’ tendency to give positive recommendations. We label each recommendation revision as an upgrade, a downgrade, or a reiteration by comparing the revised recommendation with the previous active recommendation for the stock by the revising analyst. Analysts have slightly higher tendency to issue upgrades than downgrades; 38% of the total revisions are upgrades while 36% of the revisions for downgrades. The final sample contains 1,692,435 unique news articles that met our criteria.[12] Each year in our sample, more than nearly 53% of the firms have been the primary focus of media coverage.

4 Empirical methodology

As in Jegadeesh and Kim (2010), after a recommendation revision for stock i on date t, we compute H-day buy-and-hold abnormal returns, $ABR(t, t+H)$, as follows:

$$ABR(t, t+H) = \prod_{\tau=t}^{t+H}(1 + R_{i,\tau}) - \prod_{\tau=t}^{t+H}(1 + R_{m,\tau}) \qquad (2)$$

where $R_{i,\tau}$ and $R_{m,\tau}$ are the return on stock i and the value-weighted index return, respectively. As suggested by Jegadeesh and Kim (2010), we examine the window $H = \{0, 1, 2, 21, 42, 126\}$.

[12] For the purpose of obtaining unique number of news articles, we only count as one item for news mentioning multiple firms in the content.

Herding regression

The model of Jegadeesh and Kim (2010) tests whether the market recognizes analysts' tendency to herd by examining the stock price reaction following recommendation revisions. Specifically, we run the following simple regression:

$$ABR(t, t+H) = a_H + d_H \times Deviation_t + \epsilon_{i,j,t,H} \quad (3)$$

where $Deviation_t = (NewRec_{i,j,t} - ConRec_{i,t-1})$, the magnitude of deviation of recommendation revision away from the consensus; $NewRec_{i,j,t}$ is the new recommendation level after the revision for stock i by analyst j on day t. (If there are multiple revisions on any day t for stock i, we treat each revision as a separate observation); $ConRec_{i,t-1}$ is the consensus recommendation on the day before the revision of an analyst (to ensure that the consensus is available to the analyst and the market), which is computed as the average recommendation level of all analysts. We estimate regression (3) using the Fama-MacBeth approach. Specifically, Equation (3) is estimated using all revision data within a quarter. The coefficient estimate is then the time-series average of the cross-sectional regression estimates. (Newey-West standard errors with 30 lags are computed.)[13]

Jegadeesh and Kim (2010) assume that markets are efficient such that markets are aware of the intention security analysts (i.e., whether they have an incentive or disincentive to herd). With this assumption, Jegadeesh and Kim (their proposition 3) show that, when analysts have an incentive to herd, the market's reaction to recommendation revisions that are away from the consensus (*Deviation*) will be stronger than to those closer to it (because deviation from the consensus is unex-

[13] As a robustness test, we also estimate the regressions using the pooled regression approach (with clustered standard errors by date); the results are generally stronger than those from the Fama-MacBeth approach.

pected). Conversely, when analysts have an incentive to exaggerate their differences with the consensus, the market's reaction to recommendation revisions that are away from the consensus will be weaker than those closer to it. Consequently, Jegadeesh and Kim (2010) show that the coefficient on $Deviation_t$, d_H, would be positive if the analyst has an incentive to herd. On the other hand, if analysts have an incentive to exaggerate their differences from the consensus, $d_H < 0$. d_H is therefore also called the herding coefficient. Following Jegadeesh and Kim (2010), we vary the holding period H from zero to 126 days after the revision date.

Cooper et al. (2001) argue that "lead" analysts' recommendations could influence the revisions of other analysts. We thus follow their methodology to identify lead analysts whose revision is more likely to be followed by other analysts, but lead analysts are less likely to revise following revisions by other analysts. The methodology is briefly described in the Appendix A. We next augment the above basic Model 3 to control for this analyst characteristic as well as the direction of recommendation revisions:

$$\begin{aligned} ABR(t, t+H) = a_H + d_H \times Deviation_t + b_H \times I_{multi} + c_H \times I_{single} \\ + m_H \times LeadAnalyst_j + n_H \times I \times LeadAnalyst_j + \epsilon_{i,j,t,H} \end{aligned} \tag{4}$$

where the indicator I_{multi} is either $+1$ if the revision is a multilevel upgrade (i.e., at least two-level change) or -1 if the revision is a multilevel downgrade; I_{single} is either $+1$ if the revision is a single-level upgrade (i.e., only one-level change) or -1 if the revision is a single-level downgrade; I is an indicator variable that equals $+1$ if the revision is an upgrade and -1 if the revision is a downgrade; and $LeadAnalyst$ is a dummy variable equal to 1 if the analyst is the lead analyst or zero otherwise. Other variables are defined in Model (3).

News sentiment and analyst herding As we are interested in examining the effect of media on the herding behavior of analysts in making recommendation revisions, we augment Model (4) as follows:

$$\begin{aligned}ABR(t,t+H) = {} & a_H + d_H \times Deviation_t + c_H \times Deviation_t \times NewsCoverage_{i,t-1} \\ & + t_H \times Deviation_t \times tone_{i,t-1} + s_H \times Deviation_t \times StdTone_{i,t-1} \\ & + b_H \times tone_{i,t-1} + d_H \times NewsCoverage_{i,t-1} + e_H \times StdTone_{i,t-1} \\ & + f_H \times LeadAnalyst_j + k_H \times I \times LeadAnalyst_j \\ & + i_H \times I_{multi} + j_H \times I_{single} + \epsilon_{i,j,t,H}\end{aligned} \tag{5}$$

where $tone_{i,t-1}$ is the average of news sentiment scores of all news articles for a stock over the past one quarter prior to the revision date t; $NewsCoverage_{i,t-1}$ is the log of one plus the total number of news articles over the past quarter prior to the revision date; $StdTone_{i,t-1}$ is news dispersion, which is the standard deviation of news tone scores for the firm over the past one quarter prior to the revision date. Other variables are defined in Model (3). Since stock prices are also affected by news flows prior the revision date (Tetlock; 2007), we add to the model *tone*, $NewsCoverage$, and $StdTone$ to control for these confounding effects.

Hypothesis H1a predicts that the coefficient on $Deviation \times NewsCoverage$ be positive whereas H1b predicts a positive coefficient. Hypothesis H3a predicts that the coefficient on $Deviation \times StdTone$ be positive while H3b predicts a negative coefficient. According to Hypothesis H2, the coefficient on $Deviation_t \times tone_{t-1}$ should be negative. (Note that the negative coefficient is interpreted as the positive effect of negative news sentiment on analyst herding because negative news has $tone < 0$.) To differentiate the impacts of positive and negative news sentiment on analysts' herding behavior, in Model (6), we replace *tone* with $NegNews$, which takes the value of +1 if $tone < 0$ and zero otherwise. Hypothesis H2 predicts that the coefficient on $Deviation \times NegNews$ should be positive.

5 Results

5.1 The impact of news sentiment on analysts' herding behavior

Table 2 uses the methodology of Jegadeesh and Kim (2010) to test whether analysts herd when making stock recommendations. Panel A shows thatt he coefficient on *Deviation* is 0.018 (or 1.8%), on the revision date ($H = 0$) which is statistically significant at the 1% level. The positive coefficient means that, when analysts revise their stock recommendation away from the consensus, stock returns are more positive for upgrades and more negative for downgrades. The herding coefficient increases to approximately 0.028 for longer holding periods, though the difference is not shighly ignificant. Thus, we confirm the findings of Jegadeesh and Kim (2010) that analysts herd toward the consensus and that the stock price fully incorporates for the herding effect on the revision date.

In panel B we control for the direction of the revision as well as whether the analyst is a lead analyst. The coefficients on I_{multi} and I_{single} are positive and statistically significant for all holding periods. Consistent with prior studies, in addition to deviation from the consensus, markets also react the direction of recommendation revision: stock prices are higher following upgrades and lower following downgrades. The coefficient on the interaction between *LeadAnalyst* and revision dummy is 0.006 on the revision date, with an associated t-statistic above three. This coefficient suggests that the market reacts more to recommendation revision by lead analysts.

Table 3 examines the impact of media on the herding behavior of analysts in making revisions. First, the coefficient on $Deviation \times NewsCoverage$ is negative and statistically significant for all holding periods. For firms with higher news coverage, the market's reaction to recommendation revisions that are away from the consensus is weaker than those closer to it. This finding suggests that the market recognizes that the tendency to herd among analysts is reduced when the firm has had high news coverage. When the firm is intensively covered in the spotlight, analysts' recommendations are more likely to attract attention. Since being covered in the media significantly benefits their careers (Rees et al., 2015), analysts have an incentive issue bold recommendations that are away from the consensus to increase their chance of gaining media's attention. This result is interesting not only because it shows the impact of the media, but also because it adds to the debate whether analysts herd or they just issue similar recommendations based on correlated information arrival – the information hypothesis (H1b), which predicts a positive coefficient on $Deviation \times NewsCoverage$. Our finding does not confirm the prediction of this prediction, but is more in line with the incentive hypothesis.

We next examine the most important aspect of the media – news sentiment. The coefficient on $Deviation \times Tone$ is negative and statistically significant for all holding periods; the lower the *tone* of the news sentiment, the stronger the market's reaction to recommendation revisions that are away from the consensus. This finding suggests that more pessimistic news sentiment is associated with higher tendency to herd among analysts. This result is consistent with prior research that analysts are more likely to herd for downgrades than for upgrades. We add to this literature by documenting an important moderating factor – the media sentiment.

Finally, media disagreement, as proxied by $StdTone$, also plays a role in affecting the analyst's herding behavior. Except for the 42-day window, the coefficient on $Deviation \times StdTone$ is positive and statistically significant at the 1% level. This result is consistent with the notion that the market recognizes that analysts tend to herd more when disagreement in the media is stronger. As discussed in earlier section, analysts are aware that their recommendation revisions are more likely to be sought after by investors when the future prospect of the firm is unclear (i.e., higher $StdTone$). This increasing importance of their recommendations makes it more costly for them to be wrong. Thus, this finding is more in line with Hypothesis H3a. It also suggests that news dispersion does not seem to simply represent disagreement among analysts as argued in Hypothesis H3b, which predicts a negative relation between news dispersion and analysts' tendency to herd.

Since we control for news tone in the regression, results in Table 3 suggest that the effect of $Deviation \times Tone$ on future stock returns is beyond the pure return predictability of past news sentiment. To isolate effect of negative news and thereby have a cleaner test of hypothesis H2, panel B of Table 3 replaces *tone* with $NegNews$, which is a dummy variable that takes the value of +1 if $tone < 0$ and zero otherwise. (Positive news tone is thus just the opposite regression.) We observe that the coefficient on $Deviation \times NegNews$ is indeed positive on the revision date as well as for all holding periods. This result suggests that analysts tend to herd more following negative news sentiment of the firm – consistent with Hypothesis H2. The coefficient on $Deviation \times NewsCoverage$ is also negative and statistically significant, confirming our earlier results that intense news coverage reduces the tendency to herd among analysts when making recommendation revisions. The coefficient on $Deviation \times StdTone$ is positive and statistically significant for all holding periods, except the 42-day window. Again, this result supports the prediction of hypothesis H3a that, when media disagreement is strong, analysts have stronger incentive to herd toward the consensus recommendation.

5.2 Sensitivity analysis

The impact of major corporate news

Since analysts tend to revise their recommendations around earnings announcements, we examine whether our results are particularly driven by earnings announcements by removing news items that are classified by Thomson Reuters as either earnings-related news from the firm (e.g., earnings announcements, earnings guidance, or other corporate results). We also remove news related to merger and acquisition, which is another type of major corporate events. Altinkilic and Hansen (2009) argue that analysts piggyback on news when making recommendation revisions and, once the impact of corporate news is controlled for, the effect of analysts' recommendations on stock returns disappears.[14] In a similar vein, Loh and Stulz (2011) also remove earnings-related news when they analyze the impact of influential recommendations on stock prices. Since Model 6 has *tone*, $NewsCoverage$, and $StdTone$ as independent variables, the confounding effects of news flows on future stock returns have been controlled for. Nevertheless, to examine whether our main results are driven by major corporate news, we follow Loh and Stulz (2011) to remove earnings- and merger-related news from the analysis and report regression results in Table 4.[15]

Panel A of Table 4 reports the effect of general news sentiment, *tone*, on the herding behavior of analysts. We can see that removing major news does not affect our earlier conclusions, and if any, it even makes the results stronger. In particular,

[14] Altinkilic and Hansen (2009) do not distinguish between the herding effect and piggybacking on news. Indeed, the authors acknowledge that herding among analysts can potentially be an alternative explanation for their findings.

[15] Major corporate news is classified by Thomson Reuters with topic codes RES and RESF for earnings-related news and MRG for merger and acquisition news.

the effect of $StdTone$ (a proxy for media disagreement) becomes stronger. While the coefficient on $Deviation \times StdTone$ is not significant for $H = 42$ in the sample of all news types (Table 3), it is positive and statistically significant once major news is removed. Furthermore, the coefficients on $Deviation \times NewsCovergae$ and $Deviation \times Tone$ are negative and statistically significant at the 1% level for all holding periods – consistent with hypotheses H1a and H2, respectively.

Panel B reports the effect of negative news sentiment on herding. Again, though the magnitude is lower than Table 3, the sign and statistical significance of the main coefficients do not change. Analysts have a stronger tendency to herd following negative news sentiment and strong disagreement in the media while intensive media coverage reduces their tendency to herd. Another interesting point in panel B is the coefficient on *Deviation*; it is negative on the revision date and then becomes statistically insignificant for longer holding periods (except for 21- and 42-day windows). Since the coefficient on *Deviation* is the only focus of Jegadeesh and Kim (2010), our results add to their findings that analysts tend to herd particularly when the media sentiment is negative.

In short, this subsection shows that the effect of media sentiment on herding is not specific to major news – the focus of prior research. If analysts piggyback on news, it is reasonable to expect that they do so mainly on news about the firm's fundamentals that have the highest potential impact on prices (Tetlock et al., 2008). The evidence shows that piggybacking on major news does not completely explain analysts' herding behavior. First, the fact that the findings are robust to the exclusion of fundamental news suggests that analysts do pay attention to the general sentiment of the media when making stock recommendations. Second, if piggybacking can explain analysts' herding behavior then this explanation alone is hard to reconcile with the fact that they do not tend to piggyback on positive news.

The impact of recent news

To understand the "term structure" of news sentiment, we test whether analysts are more influenced by the most recent news. Specifically, we add to regression (6) a dummy variable, $PastWeekNews$, that is equal to one if the firm has news reported in the week prior to the recommendation revision or zero otherwise. We also interact $PastWeekNews$ with $Deviation$ as well as other news variables and report the regression results in Table 5. In panel A, we can see that the effects of news coverage and news tone on herding remains negative and strong. The coefficient on ($Deviation \times NewsCoverage \times PastWeekNews$) is not significant in any holding period, suggesting that recent news coverage does not affect analysts' tendency to herd. The effect of past week's news tone is also short-term; the coefficient on ($Deviation \times Tone \times PastWeekNews$) is negative and statistically only in the first two days after the recommendation revision.

The effect of news dispersion is rather short-term only. After controlling for recent news dispersion, the coefficient on $Deviation \times StdTone$ becomes insignificant. The coefficient on $Deviation \times StdTone \times PastWeekNews$ is, however, positive and statistically significant at the 1% level. This indicates that analysts are more influenced by recent disagreement in the media when deciding whether to herd in the recommendation revisions. These results make intuitive sense because media disagreement is more likely to be resolved after a few weeks (for example, after the firm announces true earnings). When the analyst happens to make recommendation revisions during strong media disagreement times, they are more likely to herd.

Panel B reports results for negative news. The coefficient on $Deviation \times NegNews$ is negative on the revision date, but insignificant for longer holding periods. In contrast, the coefficient on ($Deviation \times NegNews \times PastWeekNews$) is positive and statistically significant for up to 42 days after the revision date. These results suggest that analysts remember recent negative news events when making decisions to herd in their recommendation revisions.

In short, this subsection has shown that analysts tend to herd more when recent disagreement in the media is strong and when the firm has had recent negative news sentiment. Analysts are more affected by long-term news coverage and the aggregate news sentiment of the firm when making recommendation revisions.

The impact of news related analysts' recommendations

Some analysts may be more vocal about their stock recommendations and try to be covered in the media. Rees et al. (2015) find that analysts who are cited in the media are more likely to be highly skilled and quality analysts. Thus, one might expect that lower quality analysts tend to herd more following the news made by those quality analysts cited in the media. Our results in the previous section could thus be driven by news articles that are related to analysts' recommendations and opinion.

The Thomson Reuters news database allows us to address this concern. Specifically, Thomson Reuters has a field indicating whether the news item is related to the stock recommendation of an analyst or a broker. We consequently remove those news items from our analysis and repeat the main results of Table 3. If analysts tend to herd following news related to the opinion of quality journalists, one would expect to observe no relationship between herding tendency and news sentiment once news related stock recommendations is removed.

Table 6 removes news related to analysts' recommendations and repeats the Fama-McBeth regression of Table 3. There are 63,358 unique news articles that are removed. In general, our main conclusions do not change. Specifically, the coefficient on $(Deviation \times Tone)$ in Panel A is negative on the revision day as well as for other holding periods. Panel B shows that the coefficient on ($Deviation \times NegNews$) is positive and statistically significant. These findings indicate that analysts have a stronger tendency to herd following negative news sentiment of the stock. The robust results suggest that the strong association between analysts' herding tendency and negative news sentiment is not driven by news articles that cite the analysts themselves. After all, if the notion that analysts herd following news that is also made by a group of quality analysts could explain our findings then this notion alone could not explain the fact that analysts do not herd more following positive news sentiment. Furthermore, since we examine analysts' recommendation revisions following negative news sentiment, it is unlikely that those analysts (who revise after the news) also influence the last quarter's news sentiment.

The effect of news dispersion on analysts' herding behavior is also robust after removing analyst-related news: the higher the media disagreement the stronger the analysts' tendency to herd. This result suggests that analysts' herding behavior is not driven by the disagreement among themselves; rather, it is more likely to be driven by the disagreement among journalists. Finally, we can also see that the negative association between news coverage and analysts' tendency to herd remains unchanged. Again, since analyst-related news has been removed, this finding indicates that the intensity of citations of analysts' opinion in the media is unlikely to explain our results on the general news coverage.

The impact of corporate press releases

Corporations often disclose information that may impact stock prices as well as analysts' research via press releases. This is especially true in sample sample, which starts after the adoption of Regulation Fair Disclosure (Reg FD) in 2000 and the Sarbanes-Oxley Act in 2002 that enforce timely and non-exclusivity disclosure of corporate information. Under these regulations, firms may try to attract the attention of the media by releasing more positive information via popular newswire services such as PR Newswire (PRN), Business Wire (BSW), GlobeNewswire (GNW), and Marketwire (MKW). In fact, approximately 40% of the news stories (675,769 items) in our sample are originated from those sources. These press releases are conveyed directly to investors from the corporation and hence, are not processed by journalists.

To examine whether the association between herding tendency and the media is driven by journalists' articles, we remove coporations' own press releases from our sample and repeat the regression in Table 3. PR Newswire has the largest number of press releases with 324,586 items. The second largest newswire service provider is Business Wire with 236,349 stories in our sample. Marketwire and GlobeNewswire have 63,793 and 51,041 stories, respectively. Since companies' press releases are removed, we should see the coefficients on $Deviation \times NewsCoverage$, $Deviation \times tone$, and $Deviation \times StdTone$ to be insignificant if there is no association between analysts' herding and news written by journalists themselves.

Table 7 reports the regression results using the sample without corporate press releases. Panel A runs regressions with *tone* as one of the controls and shows that the coefficient on $Deviation \times NewsCoverage$ is insignificant in all holding periods. Thus, after removing press releases, analysts' tendency to herd does not depend on the news coverage of the firm. However, the regression in Panel B, which replaces *tone* with $NegNews$, shows a negative coefficient on $Deviation \times NewsCoverage$, though the statistical significance is weaker than that in Table 3. These results suggest that analysts are more influenced by media hype when the general news sentiment of the company is negative. In contrast, they are not influenced by media hype when positive news sentiment dominates. This is consistent with the notion that corporations tend to release positive news to create hype in the media, which is less reliable. When the news sentiment is negative, the hype is more genuinely generated by journalists and analysts tend to pay more attention to it when making herding decisions.

Table 7 also shows consistent impact of news sentiment and news dispersion on herding. For example, the coefficient on $Deviation \times NegNews$ is positive in all holding periods, confirming our conclusions that analysts have a higher tendency to herd following the negative news sentiment of the company. Furthermore, they also herd more when disagreement in the media is stronger as shown in the positive coefficient on $Deviation \times StdTone$. These results hold even after removing the impact of press releases. It is also interesting to note in Panel B that the coefficient on $NegNews$ is insignificant. This result indicates that, unlike Tetlock (2007) and Tetlock et al. (2008), negative news has no predictive power of future returns once we remove news written by the corporations themselves. Moreover, although $NegNews$ has no predictive power, $Deviation \times NegNews$ is positive and highly significant. This suggests that market's detection of analysts' herding following negative news sentiment is not simply driven by the predictive power of $NegNews$.

6 Analysts' characteristics and herding following negative news sentiment

This section tests whether the herding behavior of analysts following negative news sentiment is consistent with the incentive hypothesis. We run the following regression:

$$
\begin{aligned}
ABR(t,t+H) = a_H &+ d_H \times Deviation_t + c_H \times Deviation_t \times NewsCoverage_{i,t-1} \\
&+ t_H \times Deviation_t \times NegNews_{i,t-1} + s_H \times Deviation_t \times StdTone_{i,t-1} \\
&+ t_H \times Deviation_t \times NewsCoverage_{i,t-1} \times Char_j \\
&+ s_H \times Deviation_t \times Tone_{i,t-1} \times Char_j \\
&+ s_H \times Deviation_t \times StdTone_{i,t-1} \times Char_j \\
&+ b_H \times Tone_{i,t-1} + d_H \times NewsCoverage_{i,t-1} + e_H \times StdTone_{i,t-1} \\
&+ f_H \times LeadAnalyst_j + k_H \times I \times LeadAnalyst_j \\
&+ i_H \times I_{multi} + j_H \times I_{single} + \epsilon_{i,j,t,H}
\end{aligned} \tag{6}
$$

where $Char_j = \{Exp, Afil, Vol\}$ are the characteristics of analysts, namely experience (Exp), investment banking affiliation ($Afil$), and analysts covering stocks with high trading volume (Vol). For analyst's experience, we count the number of years that the analyst appears in the IBES database prior to the recommendation revision date.[16] Our dummy variable, Exp, then takes the value of one if the analyst has had more than ten years of experience before the revision date, or zero otherwise.[17] For investment banking affiliation, we merge IBES with Securities Data Corporation (SDC) dataset. Following Conrad et al. (2006) and others, the analyst has an investment banking relationship with the company if the analyst's firm has any advisory role in the firm's debt or equity offerings or merger and acquisition activity. The variable $Afil$ takes the value of one if the analyst's firm has any investment banking relationship or zero otherwise. Finally, we also replace $Char_j$ with Vol, which is a

[16] In this calculation, we use the entire coverage of IBES, which starts from 1992.

[17] Our results do not qualitatively change when we use five years' experience.

dummy variable equal to one if the firm's past quarter's trading volume is in the top tercile. Specifically, at $t-1$ before the recommendation revision date, we rank stocks based on their trading volume over the past quarter. We then sort them into three bins where the first bin contains stocks with the lowest trading volume and the third bin contains stocks with the highest trading volume. We then create a dummy variable to flag stocks in the third bin and denote as Vol.

Table 8 shows regression results for analysts' experience. News sentiment is the primary characteristic of the media that differentiate the herding behavior of experienced analysts from inexperienced analysts. The coefficient on $Deviation \times NegNews \times Exp$ is positive and statistically significant, suggesting that experienced analysts are more likely to herd than other analysts following negative news sentiment. This finding is consistent with the incentive hypothesis, which says that, since reputation is hard to maintain, experienced analysts are more concerned about being wrong, and therefore tend to herd more. Moreover, experienced analysts are likely to have established connections and interests with the company that prevent them from downgrading their stock recommendations, even if the downgrade is justified by their own private information. During times of negative news sentiment, they are somewhat relieved from this pressure and more free to issue downgrade because the general consensus (both in the media and among analysts) about the firm's future prospects is also negative. Our finding is thus consistent with this line of argument. It is, however, not consistent with the overconfidence hypothesis or the ability hypothesis, which predicts no difference in the herding tendency between experienced and inexperienced analysts.[18]

[18] Our findings are also consistent with the theoretical model of Prendergast and Stole (1996) and empirical findings of Chen and Jiang (2006), who show that inexperienced analysts overweight their private information, and therefore exhibit anti-herding behavior. In contrast, Hong et al. (2000) and Clement and Tse (2004) find a positive relation between the deviation from the consensus in analysts' forecasts and experience.

The coefficients on $Deviation \times NewsCoverage \times Exp$ and $Deviation \times StdTone \times Exp$ are statistically insignificant. Thus, there is little difference in the herding behavior between experienced and inexperienced analysts during periods of high news coverage and strong media disagreement.[19]

Table 9 tests the difference in the herding behavior of investment banking affiliated analysts and non-affiliated analysts. The coefficient on $(Deviation \times NegNews \times Afil)$ is negative and statistically significant for all holding periods, suggesting that affiliated analysts are less likely to herd following negative news sentiment. Consistent with the general view behind potential incentives to herd, since affiliated analysts are reluctant to issue downgrades for firms that they have advised, they do not have an incentive to herd following negative news sentiment.[20] Affiliated analysts also tend to differentiate themselves from the consensus when media attention is high; the coefficient on $(Deviation \times NewsCoverage \times Afil)$ is negative. This finding suggests that because affiliated analysts' recommendation revisions are less likely to stand out when the firm has higher news coverage, they are more free to issue bold recommendations that are away from the consensus – consistent with the idea behind the incentive hypothesis. Affiliated analysts also tend to herd more when media disagreement is strong as shown in the positive coefficient on $(Deviation \times StdTone \times Afil)$. When media disagreement is high, the recommendation of affiliated analysts is more likely sought after, and therefore the cost of being "wrong" increases. Again,

[19] In a separate regression where we include $Deviation \times Exp$ (but not $Deviation \times NewsMeasures \times Exp$ to avoid perfect multicollinearity), the coefficient on this interaction term is positive and statistically significant in the first 2 days of holding periods, but becomes insignificant and negative for longer holding periods. These results suggest that experienced analysts tend to herd more than inexperienced analysts. Our regression results in Table 8 show that the herding tendency of experienced analysts lasts longer when the news sentiment is negative.

[20] In a separate regression where we include $Deviation \times Afil$ (but not $Deviation \times NewsMeasures \times Afil$ to avoid perfect multicollinearity), the coefficient on this interaction term is not statistically significant in the first 21 days of holding periods. These results suggest that, without conditioning on news sentiment, investment banking affiliated analysts do not herd more than non-affiliated analysts.

this is consistent with the notion of potential incentives to herd.

Table 10 tests whether analysts covering stocks with high trading volume tend to herd more following negative news sentiment. The coefficient on ($Deviation \times NegNews \times TopVol$) is negative and statistically significant. In line with the incentive hypothesis, analysts earn their commissions through generating interests in those stocks, and hence are less likely to downgrade their stock recommendations. However, they are more likely to herd when their recommendation revisions easily attract attention (i.e., when news coverage is low and when media disagreement is high). Again, these results support the notion that analysts herd because of the incentive structure.

7 Conclusion

This article has two main goals. The first is to investigate the role of the media in affecting the herding behavior of analysts when making stock recommendations. The second goal is to examine which types of analysts are more influenced by the media. Our study is one of the first to document the crucial role of media on analysts' herding tendency. Understanding the factors that affect analysts' recommendations is important because their stock recommendations can be influential in the market. Regarding the first objective, we find that analysts have lower tendency to herd toward the consensus recommendation following higher news coverage of the firm. They are, however, more likely to herd when the stock has had negative news sentiment, consistent with the notion that analysts are reluctant to stand out from the crowd when conveying negative information. Finally, following times of strong media disagreement, analysts tend to herd more toward the consensus recommendation. These findings are most consistent with the incentive hypothesis.

Motivated by the incentive hypothesis, which seems to be supported in the evidence from the first investigation, we examine three main analyst characteristics that could be more influenced by the media, namely experience, investment banking affiliation, analysts covering stocks with high trading volume. We find that experienced analysts tend to herd more following negative news sentiment, suggesting that experienced analysts are more concerned about their reputation (because the damage to their reputation as well as business connections that they have been building is higher than for inexperienced analysts when they convey negative information). Finally, analysts with investment banking affiliation and those covering high trading volume stocks (which generate higher potential trading commissions) are less likely to herd following negative news sentiment. These findings are in line with the notion of potential incentives to herd: those analysts are more reluctant to downgrade recommendations, which will hurt their business connections and compensations.

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Table 1: Summary statistics between 2003 and 2012

This table reports summary statistics for analysts' stock recommendations in the U.S. markets. The sample consists of all firms that have at least two active recommendations including one revision in the IBES database and have data in TRNA as well as CRSP. "No. firms" is the number of firms per year that meet our criteria described in the text. "sell" and "buy" are the proportions of "sell" and "buy" recommendations in the IBES database, respectively. "strong sell" and "strong buy" are the proportions of "strong sell" and "strong buy" recommendations in the IBES database, respectively. (The remaining proportion is for "hold" recommendation.) "Downgrades" or "Upgrades" is the percentage of recommendation revisions that are downgrades or upgrades. (The remaining percentage is "reiteration", which maintains the analyst's prior recommendation level.) "News Coverage (%)" is the percentage of firms with news each year. The last row reports summary statistics for the whole sample; except for "no. firms" and "no. analysts", which are total numbers, other columns are averages.

Year	No. firms	No. analysts	Strong sell (%)	Sell (%)	Buy (%)	Strong buy (%)	Downgrades (%)	Upgrades (%)	*News* Coverage (%)
2003	3876	1891	3.19	9.61	24.88	16.58	38.83	37.54	46.5
2004	3913	1763	3.77	7.74	24.53	18.81	40.48	39.97	47.2
2005	3933	1768	3.39	6.70	25.05	21.31	36.74	45.48	49.7
2006	3938	1757	4.16	7.34	24.25	19.17	37.74	38.39	56.3
2007	3921	1688	5.72	7.05	21.39	19.15	38.44	43.50	53.5
2008	3677	1722	7.85	7.96	18.11	19.15	40.57	41.64	59.0
2009	3483	1540	6.84	9.09	20.84	19.16	39.88	43.89	54.5
2010	3366	1398	2.36	6.74	25.37	21.34	38.44	42.31	50.6
2011	3235	1391	2.53	8.50	30.44	17.75	39.97	44.22	52.0
2012	3066	2045	2.08	8.72	29.35	14.53	20.05	18.44	56.5
2003–2012	5098	5359	4.19	8.06	24.42	18.32	36.05	38.01	52.48

Table 2: Regressions testing for herding

This table estimates Models (3), (4), and (6) using quarterly Fama-MacBeth regressions. The dependent variable is $ABR(t, t+H)$, which is the abnormal return on the stock after a revision of recommendation by an analyst. *Deviation* is the deviation of the recommendation revision away from the consensus, whose coefficient is called the herding coefficient. Based on the theory of Jegadeesh and Kim (2010), a positive herding coefficient suggests that analysts have a tendency to herd. Panel A shows regression estimates for Model (3) in which *Deviation* is the only control. Panel B reports regression results for Model (4), which adds I_{multi}, I_{single}, and *LeadAnalyst* to Model (3). *LeadAnalyst* is an indicator variable, which takes the value of one if the analyst is a lead analyst as defined by Cooper et al. (2001) and zero otherwise. I_{multi} is a dummy variable, which is equal to +1 if the revision is a multilevel upgrade, or −1 if the revision is a multilevel downgrade. I_{single} is a dummy variable, which is equal to +1 if the revision is a single-level upgrade, or −1 if the revision is a single-level downgrade. t-statistics are calculated using Newey-West standard errors with 30 lags are reported in parentheses.

Panel A: Model (3)

Explanatory Variables	$H=0$	1	2	21	42	126
Deviation from consensus	0.0175∗∗∗	0.0206∗∗∗	0.0211∗∗∗	0.0238∗∗∗	0.0261∗∗∗	0.0275∗∗∗
	(15.57)	(16.03)	(15.90)	(11.76)	(12.36)	(16.34)
$Adj.R^2$	0.0648	0.0694	0.0656	0.0345	0.0228	0.0097

Panel B: Model (4)

Explanatory Variables	$H=0$	1	2	21	42	126
Deviation	0.0055∗∗∗	0.0067∗∗∗	0.0069∗∗∗	0.0087∗∗∗	0.0106∗∗∗	0.0114∗∗∗
	(11.92)	(11.55)	(11.49)	(14.65)	(11.88)	(8.75)
I_{multi}	0.0216∗∗∗	0.0245∗∗∗	0.0247∗∗∗	0.0247∗∗∗	0.0235∗∗∗	0.0253∗∗∗
	(40.47)	(23.82)	(21.05)	(10.51)	(6.52)	(7.60)
I_{single}	0.0190∗∗∗	0.0221∗∗∗	0.0228∗∗∗	0.0260∗∗∗	0.0278∗∗∗	0.0288∗∗∗
	(7.51)	(7.09)	(7.20)	(6.89)	(7.93)	(10.14)
$I \times$ *LeadAnalyst*	0.0062∗∗∗	0.0075∗∗∗	0.0098∗∗∗	0.0128∗∗∗	0.0197∗∗∗	0.0129∗∗∗
	(3.90)	(3.29)	(3.11)	(2.77)	(2.67)	(3.22)
LeadAnalyst	0.0006	0.0007	0.0028	0.0080∗	0.0145∗∗	0.0081
	(0.60)	(0.62)	(1.34)	(1.91)	(2.05)	(1.33)
PastReturn	0.0024∗∗∗	0.0002	−0.0026	−0.0020	−0.0056	0.0105
	(2.63)	(0.12)	(−0.87)	(−0.35)	(−0.57)	(0.62)
$Adj.R^2$	0.1024	0.1089	0.1038	0.0576	0.0437∗	0.0332

Table 3: The impact of media on herding

This table reports estimates from regression (6), which is estimated using quarterly Fama-MacBeth approach. The dependent variable is $ABR(t, t+H)$, which is the abnormal return on the stock after a revision of recommendation by an analyst. $NegNews$ is a dummy variable indicating the negative tone of the media about the firm (it is equal to 1 if $tone < 0$ and zero otherwise. Thus, the effect of positive news sentiment is just the opposite regression). Other variables are defined in Table 3. *tone*, obtained from Thomson Reuters News Analytics (TRNA), measures the average news sentiment score for the firm over the quarter prior to the revision date. $NewsCoverage$ is log of one plus the total number of news articles covering the firm over the quarter prior to the revision date. $StdNews$ is the standard deviation of *tone*, representing the news dispersion or disagreement of media about the firm. t-statistics are calculated using Newey-West standard errors with 30 lags are reported in parentheses.

Panel A: Model (6) – the effect of general news sentiment

Explanatory Variables	$H=0$	1	2	21	42	126
$Deviation$	0.0112***	0.0147***	0.0157***	0.0172***	0.0214***	0.0199***
	(10.08)	(7.75)	(7.13)	(7.52)	(8.20)	(10.12)
$Deviation \times NewsCoverage$	−0.0031***	−0.0036***	−0.0037***	−0.0036***	−0.0033***	−0.0031***
	(−19.96)	(−10.91)	(−9.66)	(−7.90)	(−4.58)	(−3.49)
$Deviation \times Tone$	−0.0204***	−0.0190***	−0.0200***	−0.0203***	−0.0246***	−0.0346***
	(−7.66)	(−7.55)	(−7.95)	(−11.56)	(−7.27)	(−4.75)
$Deviation \times StdTone$	0.0184***	0.0174***	0.0159***	0.0159***	0.0074	0.0110***
	(10.19)	(7.24)	(4.63)	(2.60)	(0.95)	(3.04)
I_{multi}	0.0209***	0.0238***	0.0239***	0.0239***	0.0227***	0.0247***
	(35.59)	(18.96)	(16.97)	(8.93)	(5.75)	(6.89)
I_{single}	0.0188***	0.0218***	0.0226***	0.0257***	0.0272***	0.0279***
	(7.24)	(6.88)	(6.96)	(6.59)	(7.47)	(9.26)
$I \times LeadAnalyst$	0.0059***	0.0073***	0.0095***	0.0126***	0.0194***	0.0130***
	(3.90)	(3.29)	(3.09)	(2.68)	(2.60)	(3.17)
$LeadAnalyst$	0.0009	0.0010	0.0029	0.0080*	0.0142**	0.0078
	(0.87)	(0.74)	(1.37)	(1.94)	(2.06)	(1.34)
$PastReturn$	−0.0011	−0.0029	−0.0057*	−0.0058	−0.0104	0.0066
	(−0.80)	(−1.31)	(−1.75)	(−0.97)	(−1.02)	(0.41)
$NewsCoverage$	−0.0001	0.0003	0.0007**	0.0012*	0.0035***	0.0049**
	(−0.54)	(1.06)	(2.10)	(1.77)	(2.91)	(2.44)
$Tone$	0.0200***	0.0174***	0.0167***	0.0172***	0.0173***	0.0147
	(6.15)	(6.15)	(6.04)	(4.67)	(3.58)	(1.44)
$StdTone$	−0.0059***	−0.0083***	−0.0146***	−0.0243***	−0.0438***	−0.0131
	(−2.85)	(−3.26)	(−5.01)	(−3.36)	(−3.36)	(−0.81)
$Adj.R^2$	0.1131	0.1184	0.1135	0.0645	0.0506	0.0419

Table 3 continued.

Panel B: the effect of negative news sentiment						
Explanatory Variables	$H = 0$	1	2	21	42	126
Deviation	0.0037∗∗∗	0.0076∗∗∗	0.0086∗∗∗	0.0106∗∗∗	0.0148∗∗∗	0.0106∗∗∗
	(5.43)	(6.11)	(5.34)	(4.56)	(5.44)	(4.96)
$Deviation \times NewsCoverage$	−0.0029∗∗∗	−0.0034∗∗∗	−0.0034∗∗∗	−0.0035∗∗∗	−0.0032∗∗∗	−0.0030∗∗∗
	(−17.30)	(−10.93)	(−9.78)	(−7.49)	(−4.47)	(−3.12)
$Deviation \times NegNews$	0.0085∗∗∗	0.0079∗∗∗	0.0087∗∗∗	0.0096∗∗∗	0.0117∗∗∗	0.0130∗∗∗
	(7.94)	(7.30)	(7.34)	(8.13)	(4.96)	(4.00)
$Deviation \times StdTone$	0.0225∗∗∗	0.0213∗∗∗	0.0191∗∗∗	0.0183∗∗∗	0.0080	0.0146∗∗∗
	(13.54)	(9.88)	(5.87)	(2.74)	(0.89)	(3.34)
I_{multi}	0.0211∗∗∗	0.0240∗∗∗	0.0242∗∗∗	0.0242∗∗∗	0.0232∗∗∗	0.0252∗∗∗
	(38.53)	(20.44)	(18.38)	(9.50)	(6.15)	(7.55)
I_{single}	0.0189∗∗∗	0.0218∗∗∗	0.0226∗∗∗	0.0257∗∗∗	0.0273∗∗∗	0.0281∗∗∗
	(7.24)	(6.87)	(6.98)	(6.67)	(7.64)	(9.73)
$I \times LeadAnalyst$	0.0060∗∗∗	0.0073∗∗∗	0.0095∗∗∗	0.0125∗∗∗	0.0191∗∗∗	0.0130∗∗∗
	(3.89)	(3.31)	(3.12)	(2.72)	(2.63)	(3.26)
LeadAnalyst	0.0009	0.0009	0.0028	0.0076∗	0.0137∗∗	0.0077
	(0.89)	(0.75)	(1.37)	(1.94)	(2.07)	(1.36)
PastReturn	−0.0003	−0.0021	−0.0047	−0.0038	−0.0076	0.0095
	(−0.26)	(−1.00)	(−1.55)	(−0.70)	(−0.81)	(0.60)
NewsCoverage	−0.0002	0.0001	0.0005	0.0010	0.0032∗∗∗	0.0050∗∗∗
	(−1.09)	(0.55)	(1.64)	(1.41)	(2.70)	(2.57)
StdTone	−0.0119∗∗∗	−0.0139∗∗∗	−0.0207∗∗∗	−0.0325∗∗∗	−0.0531∗∗∗	−0.0240
	(−4.90)	(−5.19)	(−5.77)	(−3.94)	(−3.51)	(−1.34)
NegNews	−0.0068∗∗∗	−0.0060∗∗∗	−0.0052∗∗∗	−0.0043∗∗	−0.0035	−0.0021
	(−5.05)	(−5.23)	(−3.97)	(−2.02)	(−1.48)	(−0.57)
$Adj.R^2$	0.1118	0.1172	0.1122	0.0643	0.0501	0.0421

Table 4: Removing the impact of major corporate news

This table provides robustness tests to the main results in Table 3. It reports results from the regression (6), which is estimated using quarterly Fama-MacBeth approach and the sample does not contain earnings-related news. The dependent variable is $ABR(t, t+H)$, which is the abnormal return on the stock after a revision of recommendation by an analyst. $tone$, obtained from Thomson Reuters News Analytics (TRNA), measures the average news sentiment score for the firm over the quarter prior to the revision date. $NegNews$ is a dummy variable indicating the negative tone of the media about the firm (it is equal to 1 if $tone < 0$ and zero otherwise. Thus, the effect of positive news sentiment is just the opposite regression). $NewsCoverage$ is log of one plus the total number of news articles covering the firm over the quarter prior to the revision date. $StdNews$ is the standard deviation of $tone$, representing the news dispersion or disagreement of media about the firm. Other variables are defined in Table 3. t-statistics are calculated using Newey-West standard errors with 30 lags are reported in parentheses.

Panel A: general news sentiment, $Tone$						
Explanatory Variables	$H=0$	1	2	21	42	126
$Deviation$	0.0009*	0.0032***	0.0040***	0.0069***	0.0105***	0.0088***
	(1.86)	(9.37)	(7.17)	(6.22)	(5.05)	(5.12)
$Deviation \times NewsCoverage$	−0.0030***	−0.0033***	−0.0036***	−0.0042***	−0.0052***	−0.0045***
	(−9.03)	(−10.82)	(−12.39)	(−9.67)	(−6.13)	(−6.67)
$Deviation \times Tone$	−0.0142***	−0.0115***	−0.0109***	−0.0073***	−0.0115***	−0.0176***
	(−5.02)	(−5.50)	(−5.37)	(−4.39)	(−4.91)	(−3.20)
$Deviation \times StdTone$	0.0474***	0.0447***	0.0446***	0.0438***	0.0463***	0.0478***
	(27.76)	(29.20)	(27.74)	(26.89)	(16.57)	(13.22)
I_{multi}	0.0205***	0.0235***	0.0235***	0.0235***	0.0215***	0.0236***
	(42.07)	(22.62)	(19.82)	(9.32)	(5.89)	(7.50)
I_{single}	0.0183***	0.0213***	0.0220***	0.0251***	0.0264***	0.0275***
	(7.18)	(6.84)	(7.01)	(6.58)	(7.60)	(10.08)
$I \times LeadAnalyst$	0.0053***	0.0069***	0.0093***	0.0125***	0.0199***	0.0136***
	(3.10)	(2.92)	(2.87)	(2.49)	(2.47)	(3.31)
$LeadAnalyst$	0.0008	0.0010	0.0031	0.0084*	0.0153*	0.0089
	(0.65)	(0.69)	(1.31)	(1.75)	(1.92)	(1.33)
$PastReturn$	−0.0009	−0.0030	−0.0062*	−0.0062	−0.0114	0.0046
	(−0.72)	(−1.31)	(−1.81)	(−1.06)	(−1.10)	(0.28)
$NewsCoverage$	−0.0002	−0.0003	−0.0003	−0.0011	−0.0004	−0.0025
	(−0.25)	(−0.37)	(−0.39)	(−0.66)	(−0.15)	(−0.82)
$Tone$	0.0334***	0.0300***	0.0309***	0.0305***	0.0300***	0.0246***
	(8.41)	(8.34)	(7.93)	(7.84)	(4.23)	(2.51)
$StdTone$	−0.0071	−0.0058	−0.0077	−0.0083	−0.0186	0.0130
	(−0.93)	(−0.78)	(−1.03)	(−0.73)	(−1.03)	(0.62)
$Adj.R^2$	0.1319	0.1325	0.1257	0.0684	0.0513	0.0374

Table 4 continued.

Panel B: negative news sentiment, *NegNews*						
Explanatory Variables	$H = 0$	1	2	21	42	126
Deviation	−0.0046∗∗	−0.0013	−0.0000	0.0045∗∗	0.0054∗	0.0031
	(−1.96)	(−0.84)	(−0.02)	(2.18)	(1.91)	(0.91)
Deviation × *NewsCoverage*	−0.0028∗∗∗	−0.0030∗∗∗	−0.0034∗∗∗	−0.0042∗∗∗	−0.0048∗∗∗	−0.0042∗∗∗
	(−7.24)	(−9.01)	(−10.96)	(−8.02)	(−4.94)	(−5.56)
Deviation × *NegNews*	0.0055∗∗∗	0.0045∗∗∗	0.0041∗∗∗	0.0024∗∗	0.0051∗∗∗	0.0057∗∗∗
	(2.84)	(2.77)	(2.76)	(2.10)	(4.76)	(2.81)
Deviation × *StdTone*	0.0509∗∗∗	0.0474∗∗∗	0.0470∗∗∗	0.0458∗∗∗	0.0495∗∗∗	0.0512∗∗∗
	(22.35)	(27.25)	(25.65)	(20.55)	(14.82)	(14.33)
I_{multi}	0.0208∗∗∗	0.0237∗∗∗	0.0237∗∗∗	0.0238∗∗∗	0.0217∗∗∗	0.0240∗∗∗
	(42.45)	(22.89)	(20.03)	(9.32)	(5.90)	(7.54)
I_{single}	0.0185∗∗∗	0.0216∗∗∗	0.0223∗∗∗	0.0254∗∗∗	0.0267∗∗∗	0.0278∗∗∗
	(7.29)	(6.93)	(7.12)	(6.63)	(7.65)	(10.17)
I × *LeadAnalyst*	0.0055∗∗∗	0.0070∗∗∗	0.0095∗∗∗	0.0127∗∗∗	0.0202∗∗∗	0.0138∗∗∗
	(3.18)	(2.96)	(2.89)	(2.51)	(2.50)	(3.36)
LeadAnalyst	0.0007	0.0009	0.0030	0.0084∗	0.0153∗	0.0090
	(0.61)	(0.65)	(1.31)	(1.75)	(1.92)	(1.33)
PastReturn	0.0000	−0.0020	−0.0052	−0.0053	−0.0107	0.0056
	(0.01)	(−0.94)	(−1.59)	(−0.91)	(−1.03)	(0.35)
NegNews	−0.0004	−0.0004	−0.0005	−0.0014	−0.0009	−0.0031
	(−0.47)	(−0.52)	(−0.56)	(−0.74)	(−0.29)	(−0.97)
NewsCoverage	−0.0118∗∗∗	−0.0102∗∗∗	−0.0106∗∗∗	−0.0107∗∗∗	−0.0117∗∗∗	−0.0107∗∗
	(−6.08)	(−5.66)	(−5.38)	(−4.95)	(−2.77)	(−2.37)
StdTone	−0.0149∗∗	−0.0126∗	−0.0145∗∗	−0.0151	−0.0250	0.0066
	(−2.13)	(−1.86)	(−2.21)	(−1.41)	(−1.54)	(0.34)
$Adj.R^2$	0.1272	0.1291	0.1225	0.0670	0.0501	0.0372

Table 5: The effect of past week's news sentiment on herding

This table examines the impact of most recent news on analysts' herding behavior. The dependent variable is $ABR(t, t+H)$, which is the abnormal return on the stock after a revision of recommendation by an analyst. $PastWeekNews$ is a dummy variable that takes the value of one if the firm had news one week before the revision date. $tone$, obtained from Thomson Reuters News Analytics (TRNA), measures the average news sentiment score for the firm over the quarter prior to the revision date. $NegNews$ is a dummy variable indicating the negative tone of the media about the firm (it is equal to 1 if $tone < 0$ and zero otherwise. Thus, the effect of positive news sentiment is just the opposite regression). $NewsCoverage$ is log of one plus the total number of news articles covering the firm over the quarter prior to the revision date. $StdNews$ is the standard deviation of $tone$, representing the news dispersion or disagreement of media about the firm. Other variables are defined in Table 3. t-statistics are calculated using Newey-West standard errors with 30 lags are reported in parentheses.

Panel A: general news sentiment, $Tone$

Explanatory Variables	$H = 0$	1	2	21	42	126
$Deviation$	0.0139***	0.0168***	0.0177***	0.0196***	0.0239***	0.0215***
	(7.79)	(6.96)	(6.67)	(6.86)	(7.53)	(8.56)
$Deviation \times NewsCoverage$	−0.0044***	−0.0038***	−0.0042***	−0.0047***	−0.0041***	−0.0011
	(−9.47)	(−6.12)	(−8.18)	(−3.34)	(−3.13)	(−0.28)
$Deviation \times Tone$	−0.0037***	−0.0068***	−0.0076***	−0.0162***	−0.0230***	−0.0417**
	(−4.14)	(−3.64)	(−2.75)	(−2.96)	(−3.84)	(−2.13)
$Deviation \times StdTone$	−0.0001	−0.0060***	−0.0042	0.0004	−0.0094	−0.0156
	(−0.01)	(−2.97)	(−1.55)	(0.08)	(−1.42)	(−0.79)
$Deviation \times NewsCoverage \times PastWeekNews$	−0.0001	−0.0012**	−0.0007	−0.0003	−0.0005	−0.0029
	(−0.15)	(−2.30)	(−0.83)	(−0.15)	(−0.23)	(−0.72)
$Deviation \times Tone \times PastWeekNews$	−0.0202***	−0.0143***	−0.0146***	−0.0052	−0.0019	0.0075
	(−5.47)	(−9.59)	(−8.62)	(−0.87)	(−0.31)	(0.35)
$Deviation \times StdTone \times PastWeekNews$	0.0277***	0.0343***	0.0300***	0.0250*	0.0256*	0.0324
	(19.47)	(8.38)	(4.34)	(1.85)	(1.76)	(1.30)
I_{multi}	0.0207***	0.0236***	0.0238***	0.0237***	0.0225***	0.0244***
	(32.67)	(17.76)	(16.12)	(8.70)	(5.64)	(6.44)
I_{single}	0.0188***	0.0218***	0.0225***	0.0256***	0.0271***	0.0279***
	(7.17)	(6.81)	(6.90)	(6.57)	(7.44)	(9.21)
$I \times LeadAnalyst$	0.0058***	0.0072***	0.0094***	0.0125***	0.0193***	0.0133***
	(3.95)	(3.35)	(3.11)	(2.67)	(2.59)	(3.21)
$LeadAnalyst$	0.0010	0.0010	0.0029	0.0079**	0.0142**	0.0079
	(0.87)	(0.76)	(1.38)	(1.95)	(2.08)	(1.36)
$PastReturn$	−0.0011	−0.0028	−0.0056*	−0.0055	−0.0102	0.0068
	(−0.84)	(−1.33)	(−1.76)	(−0.95)	(−1.01)	(0.42)
$NewsCoverage$	−0.0000	0.0003	0.0007***	0.0015**	0.0034***	0.0056***
	(−0.19)	(1.54)	(2.88)	(2.41)	(3.26)	(3.01)
$Tone$	0.0199***	0.0172***	0.0165***	0.0174***	0.0172***	0.0154
	(6.17)	(6.10)	(6.02)	(4.92)	(3.66)	(1.51)
$StdTone$	−0.0061***	−0.0088***	−0.0153***	−0.0244***	−0.0436***	−0.0104
	(−3.29)	(−3.87)	(−5.21)	(−3.35)	(−3.24)	(−0.64)
$PastWeekNews$	−0.0003	0.0004	0.0005	−0.0018*	0.0003	−0.0037
	(−0.32)	(0.37)	(0.48)	(−1.90)	(0.15)	(−1.20)
$Adj.R^2$	0.1154	0.1198	0.1148	0.0659	0.0513	0.0432

Table 5 continued.

Panel B: negative news sentiment, $NegNews$						
Explanatory Variables	$H = 0$	1	2	21	42	126
$Deviation$	0.0101*** (14.27)	0.0135*** (14.18)	0.0147*** (12.39)	0.0177*** (6.59)	0.0225*** (8.50)	0.0182*** (5.06)
$Deviation \times NewsCoverage$	−0.0040*** (−16.39)	−0.0037*** (−8.85)	−0.0042*** (−11.16)	−0.0055*** (−4.45)	−0.0053*** (−4.47)	−0.0030 (−0.93)
$Deviation \times NegNews$	−0.0009** (−2.17)	−0.0007 (−0.95)	−0.0006 (−0.65)	−0.0005 (−0.50)	0.0004 (0.24)	0.0079 (1.17)
$Deviation \times StdTone$	0.0048** (2.39)	−0.0007 (−0.21)	0.0009 (0.54)	0.0070* (1.80)	−0.0030 (−0.55)	−0.0101 (−0.58)
$Deviation \times NewsCoverage \times PastWeekNews$	−0.0006*** (−3.98)	−0.0014*** (−3.17)	−0.0009 (−1.17)	0.0003 (0.17)	0.0004 (0.23)	−0.0016 (−0.59)
$Deviation \times NegNews \times PastWeekNews$	0.0116*** (10.66)	0.0106*** (14.99)	0.0115*** (17.12)	0.0130*** (10.82)	0.0144*** (7.93)	0.0074 (0.96)
$Deviation \times StdTone \times PastWeekNews$	0.0211*** (11.90)	0.0266*** (7.23)	0.0212*** (3.30)	0.0118 (0.92)	0.0099 (0.68)	0.0212 (0.89)
I_{multi}	0.0209*** (35.20)	0.0238*** (18.80)	0.0240*** (17.22)	0.0240*** (9.18)	0.0230*** (6.00)	0.0249*** (6.92)
I_{single}	0.0187*** (7.10)	0.0217*** (6.76)	0.0225*** (6.86)	0.0257*** (6.64)	0.0272*** (7.60)	0.0281*** (9.69)
$I \times LeadAnalyst$	0.0058*** (3.91)	0.0072*** (3.34)	0.0094*** (3.13)	0.0123*** (2.71)	0.0189*** (2.62)	0.0132*** (3.26)
$LeadAnalyst$	0.0010 (0.91)	0.0010 (0.80)	0.0028 (1.39)	0.0076** (1.95)	0.0137** (2.08)	0.0077 (1.36)
$PastReturn$	−0.0003 (−0.25)	−0.0021 (−1.01)	−0.0046 (−1.55)	−0.0035 (−0.66)	−0.0076 (−0.81)	0.0099 (0.63)
$NegNews$	−0.0067*** (−4.97)	−0.0059*** (−5.05)	−0.0051*** (−3.81)	−0.0042** (−2.00)	−0.0034 (−1.45)	−0.0024 (−0.65)
$NewsCoverage$	−0.0002 (−0.72)	0.0001 (0.78)	0.0005** (2.28)	0.0013** (2.06)	0.0032*** (3.05)	0.0056*** (3.08)
$StdTone$	−0.0117*** (−4.96)	−0.0140*** (−5.51)	−0.0210*** (−5.66)	−0.0326*** (−3.83)	−0.0527*** (−3.36)	−0.0220 (−1.22)
$PastWeekNews$	−0.0002 (−0.17)	0.0005 (0.42)	0.0006 (0.53)	−0.0016 (−1.68)	0.0004 (0.20)	−0.0035 (−1.13)
$Adj.R^2$	0.1146	0.1190	0.1138	0.0653	0.0509	0.0433

Table 6: Removing the impact of news related to analysts' recommendations

This table provides robustness tests to the main results in Table 3. It reports results from the regression (6), which is estimated using quarterly Fama-MacBeth approach and the sample does not contain news related analysts' recommendations. There are 63,358 unique news articles related to analysts' recommendations that are removed. The dependent variable is $ABR(t, t+H)$, which is the abnormal return on the stock after a revision of recommendation by an analyst. *tone*, obtained from Thomson Reuters News Analytics (TRNA), measures the average news sentiment score for the firm over the quarter prior to the revision date. $NegNews$ is a dummy variable indicating the negative tone of the media about the firm (it is equal to 1 if $tone < 0$ and zero otherwise. Thus, the effect of positive news sentiment is just the opposite regression). $NewsCoverage$ is log of one plus the total number of news articles covering the firm over the quarter prior to the revision date. *StdNews* is the standard deviation of *tone*, representing the news dispersion or disagreement of media about the firm. Other variables are defined in Table 3. t-statistics are calculated using Newey-West standard errors with 30 lags are reported in parentheses.

Panel A: general news sentiment, $Tone$						
Explanatory Variables	$H = 0$	1	2	21	42	126
Deviation	0.0018***	0.0035***	0.0041***	0.0067***	0.0096***	0.0089***
	(4.14)	(4.23)	(4.26)	(5.86)	(5.26)	(4.79)
Deviation × $NewsCoverage$	−0.0065***	−0.0072***	−0.0075***	−0.0079***	−0.0076***	−0.0053***
	(−13.90)	(−11.45)	(−11.50)	(−8.35)	(−6.24)	(−7.52)
Deviation × $Tone$	−0.0244***	−0.0180***	−0.0166***	−0.0083**	−0.0089*	−0.0224***
	(−4.03)	(−3.58)	(−3.90)	(−2.36)	(−1.90)	(−4.27)
Deviation × *StdTone*	0.0884***	0.0903***	0.0907***	0.0883***	0.0827***	0.0708***
	(16.73)	(15.56)	(15.77)	(10.73)	(9.53)	(11.94)
I_{multi}	0.0210***	0.0239***	0.0240***	0.0241***	0.0221***	0.0243***
	(46.04)	(26.19)	(22.73)	(9.97)	(6.21)	(7.64)
I_{single}	0.0189***	0.0219***	0.0225***	0.0256***	0.0271***	0.0279***
	(7.32)	(6.94)	(7.11)	(6.59)	(7.64)	(9.60)
I × *LeadAnalyst*	0.0056***	0.0071***	0.0095***	0.0126***	0.0196***	0.0134***
	(3.24)	(3.00)	(2.91)	(2.51)	(2.48)	(3.27)
LeadAnalyst	0.0007	0.0009	0.0029	0.0082*	0.0148*	0.0087
	(0.57)	(0.59)	(1.23)	(1.71)	(1.88)	(1.28)
$PastReturn$	−0.0007	−0.0028	−0.0059*	−0.0062	−0.0113	0.0037
	(−0.75)	(−1.40)	(−1.91)	(−1.10)	(−1.12)	(0.23)
$NewsCoverage$	0.0013**	0.0009	0.0010	−0.0000	0.0008	−0.0007
	(2.07)	(1.21)	(1.13)	(−0.00)	(0.36)	(−0.21)
$Tone$	0.0434***	0.0402***	0.0418***	0.0487***	0.0588***	0.0649***
	(5.57)	(5.59)	(5.51)	(5.65)	(3.64)	(3.11)
$StdTone$	−0.0237***	−0.0197**	−0.0219***	−0.0207*	−0.0332**	−0.0212
	(−3.39)	(−2.40)	(−2.80)	(−1.81)	(−2.26)	(−0.83)
Adj.R^2	0.1371	0.1399	0.1331	0.0706	0.0531	0.0380

Table 4 continued.

Panel B: negative news sentiment, $NegNews$						
Explanatory Variables	$H = 0$	1	2	21	42	126
$Deviation$	0.0017***	0.0034***	0.0040***	0.0067***	0.0096***	0.0088***
	(4.00)	(4.17)	(4.19)	(5.75)	(5.17)	(4.70)
$Deviation \times NewsCoverage$	−0.0069***	−0.0074***	−0.0076***	−0.0080***	−0.0077***	−0.0059***
	(−12.26)	(−10.44)	(−10.89)	(−7.20)	(−5.85)	(−8.42)
$Deviation \times NegNews$	0.0133***	0.0125***	0.0121***	0.0109***	0.0139***	0.0170***
	(4.34)	(4.32)	(4.46)	(5.78)	(6.04)	(4.94)
$Deviation \times StdTone$	0.0791***	0.0812***	0.0819***	0.0808***	0.0731***	0.0611***
	(17.56)	(15.47)	(15.53)	(9.14)	(7.58)	(7.54)
I_{multi}	0.0211***	0.0241***	0.0241***	0.0241***	0.0222***	0.0246***
	(46.15)	(27.19)	(23.48)	(10.08)	(6.35)	(8.15)
I_{single}	0.0190***	0.0219***	0.0226***	0.0256***	0.0271***	0.0279***
	(7.37)	(6.96)	(7.14)	(6.60)	(7.76)	(9.80)
$I \times LeadAnalyst$	0.0056***	0.0071***	0.0094***	0.0126***	0.0195***	0.0131***
	(3.20)	(2.98)	(2.90)	(2.52)	(2.50)	(3.30)
$LeadAnalyst$	0.0005	0.0007	0.0028	0.0079*	0.0145*	0.0084
	(0.50)	(0.55)	(1.23)	(1.71)	(1.88)	(1.26)
$PastReturn$	0.0001	−0.0020	−0.0050*	−0.0052	−0.0100	0.0054
	(0.11)	(−1.05)	(−1.72)	(−0.96)	(−1.02)	(0.34)
$NegNews$	−0.0103***	−0.0088***	−0.0090***	−0.0121***	−0.0150***	−0.0142**
	(−6.40)	(−7.49)	(−7.48)	(−5.63)	(−3.56)	(−2.28)
$NewsCoverage$	0.0027***	0.0024***	0.0024***	0.0016	0.0025	0.0011
	(4.18)	(3.02)	(2.83)	(1.21)	(1.33)	(0.40)
$StdTone$	−0.0205***	−0.0179**	−0.0195**	−0.0167	−0.0258	−0.0137
	(−2.69)	(−2.13)	(−2.41)	(−1.35)	(−1.65)	(−0.61)
$Adj.R^2$	0.1363	0.1390	0.1321	0.0709	0.0527	0.0375

Table 7: Removing the impact of corporate press releases

This table provides robustness tests to the main results in Table 3. It reports results from the regression (6), which is estimated using quarterly Fama-MacBeth approach and the sample does not contain news originated from the company via sources such as PR Newswire, Business Wire, GlobeNewswire, and Marketwire. There are a total of 675,769 news articles from those sources that are removed. The dependent variable is $ABR(t, t+H)$, which is the abnormal return on the stock after a revision of recommendation by an analyst. *tone*, obtained from Thomson Reuters News Analytics (TRNA), measures the average news sentiment score for the firm over the quarter prior to the revision date. $NegNews$ is a dummy variable indicating the negative tone of the media about the firm (it is equal to 1 if $tone < 0$ and zero otherwise. Thus, the effect of positive news sentiment is just the opposite regression). $NewsCoverage$ is log of one plus the total number of news articles covering the firm over the quarter prior to the revision date. $StdNews$ is the standard deviation of *tone*, representing the news dispersion or disagreement of media about the firm. Other variables are defined in Table 3. t-statistics are calculated using Newey-West standard errors with 30 lags are reported in parentheses.

Panel A: general news sentiment, $Tone$						
Explanatory Variables	$H=0$	1	2	21	42	126
$Deviation$	0.0035***	0.0048***	0.0051***	0.0068***	0.0094***	0.0097***
	(7.89)	(6.60)	(7.10)	(10.64)	(8.66)	(8.08)
$Deviation \times NewsCoverage$	0.0004	0.0001	−0.0007	−0.0003	0.0016	0.0013
	(0.69)	(0.23)	(−1.06)	(−0.22)	(0.89)	(0.48)
$Deviation \times Tone$	−0.0108***	−0.0102***	−0.0079**	−0.0064	−0.0186*	−0.0257**
	(−3.12)	(−3.03)	(−2.39)	(−0.73)	(−1.93)	(−1.96)
$Deviation \times StdTone$	0.0279***	0.0289***	0.0322***	0.0309***	0.0169***	0.0253*
	(5.21)	(4.63)	(4.96)	(8.00)	(3.25)	(1.69)
I_{multi}	0.0216***	0.0245***	0.0245***	0.0246***	0.0230***	0.0251***
	(44.32)	(27.03)	(22.86)	(10.07)	(6.71)	(8.42)
I_{single}	0.0192***	0.0222***	0.0229***	0.0259***	0.0274***	0.0287***
	(7.69)	(7.26)	(7.45)	(6.94)	(8.14)	(10.21)
$I \times LeadAnalyst$	0.0058***	0.0073***	0.0096***	0.0125***	0.0193***	0.0132***
	(3.22)	(2.93)	(2.86)	(2.46)	(2.47)	(3.27)
$LeadAnalyst$	0.0002	0.0004	0.0024	0.0073	0.0140*	0.0086
	(0.25)	(0.32)	(1.13)	(1.63)	(1.84)	(1.29)
$PastReturn$	0.0020**	−0.0004	−0.0034	−0.0030	−0.0073	0.0069
	(2.42)	(−0.21)	(−1.18)	(−0.55)	(−0.75)	(0.41)
$NewsCoverage$	−0.0007	−0.0014	−0.0019**	−0.0016	−0.0022	−0.0003
	(−1.18)	(−1.63)	(−2.35)	(−1.21)	(−0.74)	(−0.08)
$Tone$	−0.0007	−0.0004	0.0018	0.0011	−0.0029	−0.0152***
	(−0.16)	(−0.10)	(0.45)	(0.22)	(−0.83)	(−2.60)
$StdTone$	0.0088	0.0133	0.0138	0.0103	0.0188	0.0098
	(0.85)	(1.18)	(1.33)	(0.72)	(0.80)	(0.33)
$Adj.R^2$	0.1253	0.1294	0.1224	0.0662	0.0487	0.0345

Table 4 continued.

Panel B: negative news sentiment, $NegNews$						
Explanatory Variables	$H = 0$	1	2	21	42	126
$Deviation$	0.0034∗∗∗	0.0047∗∗∗	0.0051∗∗∗	0.0067∗∗∗	0.0093∗∗∗	0.0096∗∗∗
	(7.46)	(6.35)	(6.89)	(10.56)	(8.69)	(8.08)
$Deviation \times NewsCoverage$	−0.0008	−0.0010∗∗	−0.0014∗∗∗	−0.0010∗∗	−0.0004	−0.0021∗
	(−1.60)	(−1.95)	(−2.67)	(−1.98)	(−0.67)	(−1.80)
$Deviation \times NegNews$	0.0196∗∗∗	0.0201∗∗∗	0.0187∗∗∗	0.0195∗∗∗	0.0245∗∗∗	0.0224∗∗∗
	(7.15)	(7.78)	(8.63)	(6.55)	(6.18)	(4.16)
$Deviation \times StdTone$	0.0238∗∗∗	0.0244∗∗∗	0.0272∗∗∗	0.0266∗∗∗	0.0137∗∗∗	0.0279∗∗∗
	(4.06)	(3.62)	(4.02)	(9.20)	(4.13)	(2.72)
I_{multi}	0.0215∗∗∗	0.0244∗∗∗	0.0244∗∗∗	0.0244∗∗∗	0.0228∗∗∗	0.0251∗∗∗
	(45.51)	(25.79)	(21.98)	(9.89)	(6.60)	(8.37)
I_{single}	0.0192∗∗∗	0.0222∗∗∗	0.0229∗∗∗	0.0260∗∗∗	0.0274∗∗∗	0.0288∗∗∗
	(7.67)	(7.23)	(7.44)	(6.99)	(8.21)	(10.39)
$I \times LeadAnalyst$	0.0060∗∗∗	0.0074∗∗∗	0.0097∗∗∗	0.0125∗∗∗	0.0193∗∗∗	0.0131∗∗∗
	(3.16)	(2.89)	(2.85)	(2.48)	(2.48)	(3.18)
$LeadAnalyst$	0.0003	0.0005	0.0025	0.0075	0.0141∗	0.0088
	(0.32)	(0.37)	(1.16)	(1.67)	(1.87)	(1.33)
$PastReturn$	0.0021∗∗	−0.0004	−0.0034	−0.0030	−0.0073	0.0068
	(2.40)	(−0.20)	(−1.17)	(−0.55)	(−0.75)	(0.41)
$NegNews$	−0.0003	−0.0006	−0.0016	0.0036	0.0054	0.0246∗∗∗
	(−0.14)	(−0.22)	(−0.64)	(0.73)	(1.13)	(2.98)
$NewsCoverage$	−0.0006	−0.0012	−0.0014	−0.0011	−0.0022	−0.0017
	(−0.55)	(−1.01)	(−1.22)	(−0.60)	(−0.69)	(−0.45)
$StdTone$	0.0077	0.0121	0.0123	0.0061	0.0151	0.0024
	(0.68)	(0.97)	(1.06)	(0.37)	(0.60)	(0.08)
$Adj.R^2$	0.1270	0.1311	0.1238	0.0674	0.0500	0.0357

Table 8: Analysts' experience and herding

This table tests whether experienced analysts are more likely to herd when making recommendation revisions. The dependent variable is $ABR(t, t+H)$, which is the abnormal return on the stock after a revision of recommendation by an analyst. Exp is a dummy indicator whether the analyst has had more than five years of experience in the job. $tone$, obtained from Thomson Reuters News Analytics (TRNA), measures the average news sentiment score for the firm over the quarter prior to the revision date. $NegNews$ is a dummy variable indicating the negative tone of the media about the firm (it is equal to 1 if $tone < 0$ and zero otherwise. Thus, the effect of positive news sentiment is just the opposite regression). $NewsCoverage$ is log of one plus the total number of news articles covering the firm over the quarter prior to the revision date. $StdNews$ is the standard deviation of $tone$, representing the news dispersion or disagreement of media about the firm. $PastWeekNews$ is a dummy variable that takes the value of one if the firm had news one week before the revision date. Other variables are defined in Table 3. t-statistics are calculated using Newey-West standard errors with 30 lags are reported in parentheses.

Explanatory Variables	$H = 0$	1	2	21	42	126
$Deviation$	0.0069***	0.0107***	0.0119***	0.0147***	0.0190***	0.0142***
	(8.05)	(10.42)	(8.94)	(6.43)	(7.49)	(6.81)
$Deviation \times NewsCoverage$	−0.0035***	−0.0040***	−0.0041***	−0.0040***	−0.0035***	−0.0022***
	(−14.40)	(−9.10)	(−7.28)	(−6.31)	(−2.98)	(−2.59)
$Deviation \times NegNews$	0.0066***	0.0056***	0.0067***	0.0100***	0.0116***	0.0113***
	(16.01)	(9.81)	(6.92)	(5.48)	(3.29)	(3.35)
$Deviation \times StdTone$	0.0188***	0.0182***	0.0164***	0.0111	0.0002	−0.0011
	(6.31)	(4.99)	(3.26)	(1.31)	(0.02)	(−0.18)
$Deviation \times NewsCoverage \times Exp$	0.0008	0.0011	0.0010	−0.0002	−0.0009	−0.0049**
	(0.92)	(1.24)	(0.94)	(−0.12)	(−0.39)	(−2.18)
$Deviation \times NegNews \times Exp$	0.0075**	0.0091***	0.0084**	0.0032	0.0047	0.0095*
	(2.19)	(2.58)	(2.18)	(1.06)	(0.95)	(1.71)
$Deviation \times StdTone \times Exp$	−0.0012	−0.0045	−0.0056	0.0062	0.0092	0.0402***
	(−0.17)	(−0.66)	(−0.64)	(0.64)	(0.55)	(2.56)
I_{multi}	0.0211***	0.0240***	0.0240***	0.0239***	0.0225***	0.0248***
	(36.74)	(19.11)	(16.65)	(8.82)	(5.62)	(7.43)
I_{single}	0.0191***	0.0221***	0.0227***	0.0256***	0.0268***	0.0283***
	(7.58)	(7.15)	(7.20)	(6.89)	(7.87)	(10.30)
$I \times LeadAnalyst$	0.0046***	0.0059***	0.0084***	0.0118***	0.0190***	0.0120***
	(4.48)	(3.50)	(3.09)	(2.62)	(2.51)	(2.90)
$LeadAnalyst$	0.0012	0.0014	0.0038	0.0090*	0.0153*	0.0062
	(1.08)	(0.96)	(1.51)	(1.88)	(1.94)	(1.09)
$PastReturn$	−0.0004	−0.0021	−0.0046	−0.0035	−0.0073	0.0097
	(−0.27)	(−0.99)	(−1.53)	(−0.67)	(−0.79)	(0.61)
$NewsCoverage$	0.0000	0.0004*	0.0009***	0.0016**	0.0038***	0.0049**
	(0.08)	(1.75)	(2.59)	(2.04)	(2.89)	(2.25)
$NegNews$	−0.0071***	−0.0062***	−0.0052***	−0.0042*	−0.0036	−0.0024
	(−6.07)	(−6.16)	(−4.21)	(−1.74)	(−1.30)	(−0.62)
$StdTone$	−0.0086***	−0.0108***	−0.0177***	−0.0294***	−0.0501***	−0.0213
	(−3.85)	(−4.50)	(−4.62)	(−3.35)	(−3.27)	(−1.30)
Exp	−0.0001	−0.0001	−0.0015	−0.0027	−0.0033	0.0051**
	(−0.04)	(−0.14)	(−1.13)	(−1.10)	(−0.85)	(2.41)
$Adj.R^2$	0.1141	0.1191	0.1143	0.0657	0.0512	0.0435

Table 9: Investment Banking Affiliation and herding

This table tests whether investment banking affiliated analysts are more likely to herd. The dependent variable is $ABR(t, t+H)$, which is the abnormal return on the stock after a revision of recommendation by an analyst. $Afil$ is a dummy indicator whether the analyst's firm has an investment banking relationship with the firm. $tone$, obtained from Thomson Reuters News Analytics (TRNA), measures the average news sentiment score for the firm over the quarter prior to the revision date. $NegNews$ is a dummy variable indicating the negative tone of the media about the firm (it is equal to 1 if $tone < 0$ and zero otherwise. Thus, the effect of positive news sentiment is just the opposite regression). $NewsCoverage$ is log of one plus the total number of news articles covering the firm over the quarter prior to the revision date. $StdNews$ is the standard deviation of $tone$, representing the news dispersion or disagreement of media about the firm. $PastWeekNews$ is a dummy variable that takes the value of one if the firm had news one week before the revision date. Other variables are defined in Table 3. t-statistics are calculated using Newey-West standard errors with 30 lags are reported in parentheses.

Explanatory Variables	$H = 0$	1	2	21	42	126
$Deviation$	0.0065***	0.0102***	0.0113***	0.0140***	0.0181***	0.0130***
	(7.22)	(11.55)	(10.03)	(6.42)	(8.30)	(5.13)
$Deviation \times NewsCoverage$	−0.0032***	−0.0037***	−0.0037***	−0.0038***	−0.0034***	−0.0033***
	(−22.22)	(−13.85)	(−11.53)	(−9.04)	(−4.80)	(−2.91)
$Deviation \times NegNews$	0.0090***	0.0085***	0.0094***	0.0109***	0.0131***	0.0140***
	(7.98)	(8.28)	(8.54)	(9.76)	(5.46)	(4.55)
$Deviation \times StdTone$	0.0183***	0.0174***	0.0149***	0.0124*	0.0012	0.0102**
	(8.50)	(6.72)	(4.50)	(1.74)	(0.13)	(2.38)
$Deviation \times NewsCoverage \times Afil$	−0.1815***	−0.1912***	−0.1796***	−0.3042***	−0.3778***	−1.2081***
	(−4.14)	(−4.18)	(−4.63)	(−3.16)	(−3.84)	(−4.78)
$Deviation \times NegNews \times Afil$	−0.2379***	−0.2036**	−0.1823**	−0.2781*	−0.2683***	−0.4851**
	(−2.94)	(−2.10)	(−2.37)	(−1.79)	(−2.78)	(−2.34)
$Deviation \times StdTone \times Afil$	2.1115***	2.1887***	2.0343***	3.2663***	3.7318***	12.1369***
	(4.05)	(3.99)	(4.45)	(3.27)	(3.56)	(4.86)
I_{multi}	0.0210***	0.0239***	0.0240***	0.0241***	0.0230***	0.0250***
	(36.15)	(18.77)	(17.13)	(9.30)	(5.99)	(7.35)
I_{single}	0.0189***	0.0219***	0.0226***	0.0257***	0.0273***	0.0279***
	(7.35)	(6.96)	(7.09)	(6.77)	(7.72)	(10.17)
$I \times LeadAnalyst$	0.0060***	0.0074***	0.0096***	0.0126***	0.0192***	0.0131***
	(3.82)	(3.26)	(3.10)	(2.73)	(2.64)	(3.29)
$LeadAnalyst$	0.0008	0.0009	0.0028	0.0075*	0.0138**	0.0076
	(0.82)	(0.71)	(1.34)	(1.90)	(2.03)	(1.32)
$PastReturn$	−0.0004	−0.0022	−0.0048	−0.0038	−0.0080	0.0089
	(−0.28)	(−1.01)	(−1.55)	(−0.72)	(−0.86)	(0.56)
$NewsCoverage$	0.0000	0.0004*	0.0008***	0.0014*	0.0034***	0.0047**
	(0.05)	(1.82)	(2.62)	(1.94)	(2.82)	(2.07)
$NegNews$	−0.0072***	−0.0063***	−0.0054***	−0.0047**	−0.0042	−0.0033
	(−6.04)	(−6.12)	(−4.27)	(−1.97)	(−1.57)	(−0.86)
$StdTone$	−0.0089***	−0.0112***	−0.0183***	−0.0295***	−0.0500***	−0.0202
	(−4.00)	(−4.71)	(−4.59)	(−3.24)	(−3.14)	(−1.22)
$Afil$	0.0417***	0.0439***	0.0336***	0.0479***	0.0487***	0.1518***
	(2.88)	(2.87)	(2.95)	(2.48)	(3.18)	(3.53)
$Adj.R^2$	0.1157	0.1213	0.1155	0.0659	0.0509	0.0448

Table 10: Trading volume and herding

This table tests whether analysts are more likely to herd on stocks with high trading volume. The dependent variable is $ABR(t, t+H)$, which is the abnormal return on the stock after a revision of recommendation by an analyst. Vol is a dummy indicator whether the trading volume of the stock is in the highest tercile bracket. *tone*, obtained from Thomson Reuters News Analytics (TRNA), measures the average news sentiment score for the firm over the quarter prior to the revision date. $NegNews$ is a dummy variable indicating the negative tone of the media about the firm (it is equal to 1 if $tone < 0$ and zero otherwise. Thus, the effect of positive news sentiment is just the opposite regression). $NewsCoverage$ is log of one plus the total number of news articles covering the firm over the quarter prior to the revision date. $StdNews$ is the standard deviation of *tone*, representing the news dispersion or disagreement of media about the firm. $PastWeekNews$ is a dummy variable that takes the value of one if the firm had news one week before the revision date. Other variables are defined in Table 3. t-statistics are calculated using Newey-West standard errors with 30 lags are reported in parentheses.

Explanatory Variables	$H = 0$	1	2	21	42	126
$Deviation$	0.0031∗∗∗	0.0059∗∗∗	0.0058∗∗∗	0.0062∗∗∗	0.0059∗∗	0.0013
	(2.49)	(6.45)	(6.12)	(4.09)	(2.03)	(0.21)
$Deviation \times NewsCoverage$	0.0001	0.0004	0.0017	0.0038∗	0.0083	0.0052
	(0.02)	(0.46)	(1.42)	(1.84)	(1.62)	(1.20)
$Deviation \times NegNews$	0.0114∗∗∗	0.0115∗∗∗	0.0130∗∗∗	0.0156∗∗∗	0.0205∗∗∗	0.0206∗∗∗
	(11.71)	(10.77)	(8.28)	(7.33)	(5.12)	(3.98)
$Deviation \times StdTone$	0.0108	0.0070	−0.0013	−0.0089	−0.0370	−0.0085
	(1.37)	(1.08)	(−0.17)	(−0.62)	(−1.37)	(−0.50)
$Deviation \times NewsCoverage \times TopVol$	−0.0027∗∗	−0.0034∗∗∗	−0.0047∗∗∗	−0.0062∗∗∗	−0.0097∗∗	−0.0056∗
	(−2.18)	(−3.86)	(−4.69)	(−3.63)	(−2.44)	(−1.72)
$Deviation \times NegNews \times TopVol$	−0.0038∗∗∗	−0.0046∗∗∗	−0.0056∗∗∗	−0.0067∗∗∗	−0.0107∗∗∗	−0.0092∗
	(−5.11)	(−6.76)	(−6.28)	(−3.22)	(−3.59)	(−1.94)
$Deviation \times StdTone \times TopVol$	0.0086	0.0115∗	0.0185∗∗∗	0.0209∗∗	0.0427∗∗	0.0133
	(0.95)	(1.89)	(2.88)	(2.24)	(1.98)	(0.74)
I_{multi}	0.0210∗∗∗	0.0239∗∗∗	0.0240∗∗∗	0.0239∗∗∗	0.0226∗∗∗	0.0248∗∗∗
	(40.40)	(20.35)	(18.04)	(9.45)	(5.89)	(7.31)
I_{single}	0.0188∗∗∗	0.0218∗∗∗	0.0226∗∗∗	0.0257∗∗∗	0.0272∗∗∗	0.0281∗∗∗
	(7.36)	(6.99)	(7.11)	(6.77)	(7.64)	(9.51)
$I \times LeadAnalyst$	0.0060∗∗∗	0.0074∗∗∗	0.0096∗∗∗	0.0127∗∗∗	0.0198∗∗∗	0.0135∗∗∗
	(4.22)	(3.45)	(3.19)	(2.77)	(2.67)	(3.17)
$LeadAnalyst$	0.0009	0.0010	0.0029	0.0078∗	0.0141∗∗	0.0078
	(0.89)	(0.77)	(1.38)	(1.93)	(2.05)	(1.31)
$PastReturn$	−0.0005	−0.0023	−0.0050	−0.0044	−0.0087	0.0091
	(−0.38)	(−1.07)	(−1.60)	(−0.82)	(−0.90)	(0.57)
$NewsCoverage$	0.0006∗	0.0012∗∗∗	0.0020∗∗∗	0.0037∗∗∗	0.0074∗∗∗	0.0097∗∗∗
	(1.69)	(3.07)	(3.05)	(2.56)	(2.97)	(3.27)
$NegNews$	−0.0072∗∗∗	−0.0064∗∗∗	−0.0056∗∗∗	−0.0047∗∗	−0.0044∗	−0.0035
	(−5.85)	(−5.97)	(−4.37)	(−2.04)	(−1.73)	(−0.93)
$StdTone$	−0.0085∗∗∗	−0.0113∗∗∗	−0.0190∗∗∗	−0.0325∗∗∗	−0.0545∗∗∗	−0.0254
	(−3.97)	(−4.75)	(−4.55)	(−3.29)	(−3.09)	(−1.59)
$TopVol$	−0.0021∗∗	−0.0030∗∗∗	−0.0048∗∗∗	−0.0097∗∗∗	−0.0161∗∗∗	−0.0214∗∗∗
	(−1.99)	(−3.00)	(−2.74)	(−3.15)	(−3.03)	(−6.59)
$Adj.R^2$	0.1165	0.1210	0.1160	0.0673	0.0524	0.0460

Appendices

A Identifying lead analysts

We briefly summarize the methodology of Cooper, Day and Lewis (2001) to identify lead analysts. Prior to each recommendation revision, we identify two recommendation revisions by two different analysts (different from the revising analyst). We then count the number of days between these two recommendations and the revision date (denoted by T_{-1} and T_{-2}). Similarly, we also identify two recommendation revisions by two different analysts after the revision date and denote by T_{+1} and T_{+2} the number of days between those revisions and the revision date. The leader-follower ratio (LFR) is then:

$$LFR_j = \frac{\sum_{k=1}^{K}(T_{-1,j,k} + T_{-2,j,k})}{\sum_{k=1,j,k}^{K}(T_1 + T_{2,j,k})} \tag{7}$$

where k indexes each recommendation made by analyst j during the sample period. A lead analyst has an LFR greater than one because he or she would systematically release revisions before other analysts. Cooper et al. (2001) show that this ratio follows an F distribution with both degrees of freedom equal to $4K$. Following their suggestion, which was also adopted by Jegadeesh and Kim (2010), we label analysts with LFR ratios in the top 10 percentile of the F distribution as "lead" analysts. Following this rule, the average LFR ratio for lead analysts is 6.12 while that for other analysts is 0.83.