Do Analysts Learn from the News Media? Evidence from a Natural Experiment

Somnath Das
University of Illinois Chicago
sdas@uic.edu

Rong (Irene) Zhong
University of Illinois Chicago
ronzhong@uic.edu

Current Draft: January 2024

Preliminary Draft.

Do Analysts Learn from the News Media?
Evidence from a Natural Experiment

ABSTRACT

This study examines whether analysts learn from local media about covered firms, and if so, what they learn, and the extent to which the learning affects their private research. Exploiting staggered county-level local newspaper closures as adverse shocks to firms' news coverage, we provide plausible causal evidence that unexpected loss of local firms' media coverage leads to a decline in their analysts' research quality. Specifically, analysts produce less frequent, timely, and accurate forecasts after their covered firms lose media coverage. Markets also react less strongly to these analysts' earnings forecast revisions and stock recommendation changes. Further investigation into the content and tone of the news reveals that the media helps reduce analysts' optimistic biases: analysts learn more from the media when it initiates the *first* coverage of firms and conveys *negative* sentiment on firms' earnings news or legal proceedings. Analysts also rely more on media news when they are less experienced, covering more complex firms while receiving less resource support from affiliated brokerages. Overall, our findings suggest that both the frequency of news flows and the tone of the news contribute to the informativeness of analysts' research.

***Keywords*:** Financial Analysts, Information Intermediary, Learning, Local news media, Newspaper Closures, News coverage.

***JEL classifications*:** G10, G14, G20, M40, M41,

1. INTRODUCTION

Sell-side analysts are an important financial intermediary in collecting and disseminating firm information to capital market participants (e.g., Womack 1996; Jegadeesh et al. 2004; Ramnath et al. 2008). Despite their importance in ensuring a well-functioning capital market, how analysts conduct their private research and what factors impact their decision-making remains largely a "black box" (Brown et al. 2014; Ramnath, Rock and Shane 2008). Similarly, financial journalists act as intermediaries, akin to analysts, by uncovering new and timely information about companies and distributing such news to broader audiences (e.g., Miller 2006; Tetlock 2007; Bushee et al. 2010). However, financial journalists possess distinct incentives and characteristics compared to analysts. These differences empower journalists to potentially produce accurate and timely news articles about firms, often with exclusive content (Call et al. 2022). This study aims to investigate whether analysts actively glean insights from local media regarding the firms they cover. If so, what do analysts learn, and to extent to which the learning affects their research quality. [1]

Our inquiry is partly motivated by recent calls to have a more comprehensive understanding of the information flow in financial markets (Miller and Skinner 2015; Call et al. 2022). Prior research generally considers sell-side analysts and financial journalists as two independent information intermediaries in capital markets. However, little is known whether and how the information production of the two intermediaries interacts, e.g., do they substitute or complement each other? Can analysts learn and benefit from media news when making earnings forecasts or stock recommendations of covered firms? If so, what type of news is most helpful and why? A fuller understanding of these questions can shed new light into the "black box" of decision process of financial analysts (e.g., Brown et al. 2015; Bradshaw et al. 2018) and the "overlapping and differing" incentives of the financial media (Miller and Skinner 2015, p. 233). Our study is also timely and relevant as analysts' private access to firm management has been largely restricted by the passage of Regulation FD (Bushee et al. 2004). [2]

[1] In this paper, our focus is primarily on the "news" media rather than on "social" media such as twitter etc. which has also given rise to a burgeoning literature on the role of social media in financial markets.
[2] In August 2000, the Securities and Exchange Commission (SEC) passed Regulation FD (Reg FD) that prohibits firms from disclosing material information to select groups of market participants, including analyst.

Financial journalists likely produce timelier and more credible news than analysts, making them a potential source for analysts to gain early and exclusive insights about covered firms when generating their own reports. Timeliness is one important factor for journalism. Research shows that financial journalists have superior ability in gathering firm-related information from a variety of public sources, including company press releases, Form 8-K reports, public earnings conference calls, and corporate 10-K or 10-Q reports (Miller and Skinner 2015). Additionally, nearly 63% of financial journalists report that they also use private communications (e.g., phone calls) with company managements or media relations officers to obtain exclusive insights or tips about firms' breaking news (Call et al. 2022). Furthermore, media news are likely more accurate. Kothari et al. (2009) posit that journalists are more credible than analysts because they do not have strong economic ties and relationships with individual firms. In contrast to analysts whose compensation is tied to commissions and have incentives to produce optimistic forecasts to promote market trading, journalists are evaluated primarily based on the *accuracy* of news stories (Call et al. 2022). Thus, financial journalists have strong incentives to produce accurate and informative articles to satisfy the needs of informed readers including analysts. Overall, the timely, accurate, and credible nature of media news and their in-depth, exclusive content make the media an ideal source for analysts to gain private, firm-relevant insights about their covered firms, and use that insights to improve the quality of their private research.[3]

However, there are also plausible reasons media news does not influence the quality of analysts' private research. First, analysts have different objective functions that may prevent them from learning from media news. Analysts may purposely bias their forecasts upward due to compensation incentives or to maintain relationships with managers (Francis and Philbrick 1993; Darrough and Russell 2002; Richardson et al. 2004). Even though analysts are aware of media news as a potential information source, they may not actively incorporate that information into their research. Second, analysts are well-educated professionals and sophisticated information users, making it unnecessary for them to rely upon the news media. Analysts'

[3] The dissemination of information plays a crucial role in shaping investor expectations financial markets (Tetlock 2007; Da et al. 2011; Tetlock 2015). However, given that information dissemination and information production may often be intertwined, empirically it has been challenging to discriminate between the two and is not the focus of this paper.

strong resource support (e.g., technology support, data analyzing tool, etc.,) from their affiliated brokerages increase their ability to collect and analyze firm statistics across a large set of firms (Clement 1999). Third, despite the restriction on selective disclosure enacted through Reg FD, analysts may still have some private communications with firm management in the "backroom chat" (Brown et al. 2015). Hence, whether and the extent to which analysts rely upon and learn from news media is an empirical question.

The objective of our study is to empirically evaluate whether analysts actively learn from media news when conducting their private research. A traditional OLS regression that associates a firm's media coverage to its analysts' forecast properties is subject to endogeneity concerns, as both measures are likely correlated with unobservable firm fundamentals. For example, more transparent firms may be associated with both greater media coverage and more accurate analyst forecasts. To circumvent endogeneity concerns, we exploit staggered county-level newspapers closures as plausibly exogenous shocks to a firm's news coverage and examine whether the unexpected loss of the firm's news coverage affects its analysts' research quality. One important benefit of our setting is that these closure events are unanticipated by firms and their analysts, hence providing a valid experiment to examine the impact of exogenous loss of media coverage on analyst research. Another advantage is that these events are staggered *across firms* and *over time*. Since one analyst can cover multiple firms, a coverage shock may only affect some firms covered by an analyst, allowing a tighter identification of the treatment effect by comparing the changes in research quality between treatment and control firms covered by the same analyst. This feature allows us to hold analyst-level characteristics constant, better isolating the treatment effect attributed to local newspaper closures.

Our main analyses examine the impact of local newspaper closures on analysts' research quality using a difference-in-differences design. We find that analysts produce less frequent, timely, and accurate forecasts following the closure events of covered firms. Markets also react less strongly to analysts' earnings forecast revision and stock recommendation changes. Our analyses using different proxies for the quality of analyst research outputs provide consistent evidence that the exogenous loss of media coverage of firms, due to the closures of local newspapers, adversely affects analysts' research quality. Our results hold after controlling for firm, firm-analyst and year fixed effects, suggesting that our findings are unlikely attributed to constant observable firm characteristics, firm-analyst matching, or time trends. Overall, our results support the notion that analysts do learn from local media and the learning improves the quality of their private research about the covered firms.

Next we investigate what do analysts learn from the media. We retrieve detailed news information from Ravenpack database and exploit variation in news content, news tone and news subcategories. Research suggests that initial news coverage of firms conveys new information than repetitive coverage of firms (e.g., Dai et al. 2015). We find that newspaper closures have a greater impact on analysts' research when the media initiates first coverage of treatment firms. We then partition our sample based on the average tone of news about treatment firms, and show that local media has a greater impact on analyst research when it conveys a negative tone about firm news. We further break down the type of media news based on the categories of news reported by Ravenpack, and find that analysts research is affected most by local news related to a firm's revenue/earnings, or legal proceedings. Overall, our evidence is consistent with the notion that media helps reduce optimistic biases in analyst research: analysts primarily learn from negative news related to a firms' earnings or legal proceedings. Our finding is also consistent with prior research that media pessimism can predict stock market movement (Tetlock 2007).

We further explore what type of analysts benefit more from media news. We posit that analysts are more likely rely on local news when they face higher uncertainty about the covered firms or lack resource support from their brokerages to conduct independent research. Consistent with our expectations, we find that analysts who follow more complex firms (e.g., firms operating across multiple business segments) and firms with greater reporting opacity experience larger decline in research quality after these firms' local newspaper shutdowns. Further, our results show that the decrease in analysts' research quality is more pronounced when analysts have less experience with the covered firm or affiliate with smaller brokerages. These results reinforce our main findings and delineate the conditions where analysts can learn and benefit more from firm news reported by the local media.

We conduct a range of additional analyses to enhance our inferences and ensure the robustness of our findings. In additional to a difference-in-differences analyses, we also bring in detailed coverage data from Ravenpack and conduct an OLS regression. One advantage of using OLS regressions is that we can analyze the impact of media coverage and media sentiment separately within one single regression. We find that both the frequency of the news flow and the tone of news matter in analysts' research. Both news coverage and tone contribute to the accuracy of analyst forecasts. Consistent with our prior findings, we find the tone of the media is especially effective in eliminating the optimistic biases in analysts' forecasts. Similarly, we find that news coverage and tone are associated with a greater market reaction to analysts' forecast revisions, especially for those downgrading revisions.

This paper makes several contributions to literature. First, and foremost, this paper contributes to the literature on unraveling the 'black box' of analysts' production function. Second, ours is the first paper to document that not only is the frequency but also the 'tone' of the news content is systematically associated with analysts forecasting behavior. Third, to the best of our knowledge, ours is the first paper to provide evidence that there is significant cross-sectional variation in the extent to which analysts incorporate information from the news media. Fourth, our evidence that financial analysts benefit from the news media suggests that such evidence is consistent with their role as information intermediaries that disseminate rather than produce information.

Finally, we add to the emerging body of literature that examines the interaction between different sources of information, and particularly the role of media in financial markets. In this realm, our paper extends and complements a related work by Bradshaw et al. (2021) who examine the association between sell-side analyst's stock recommendations and soft information in firm-specific news coverage [4] Specifically, given that analysts' recommendations are generally sticky but are also a multifaceted output that is driven by among other things, analysts' incentives such as investment banking relationships (e.g., Lin and McNichols 1998; Barber et al. 2004), they may not be a representative outcomes where news media is likely to have a direct impact. Therefore, unlike Bradshaw et al. (2021), we provide direct evidence of analysts' use of news media by examining whether their use or lack of use of news media affects their

[4] Specifically, they document that more frequent recent news coverage is associated with more frequent recommendation revisions and stronger market reactions to analysts' recommendation revisions.

research output other than recommendations. More fundamentally, we complement Bradshaw et al. (2021) by using an exogenous shock to the news media which enhances our ability to draw causal inferences on analysts' learning from the news media. Moreover, we examine settings in which analysts are more reliant on the news media and whether the news content i.e., the sentiment of the news has an impact on analysts' forecast properties. These extensions complement prior literature and add to the empirical regularities that provide a more nuanced understanding of the 'black box' of analysts 'decision-making.

The rest of the paper proceeds as follows. In Section 2, we discuss the institutional background and develop testable hypotheses that provide a basis for our empirical specification of the relationship. Section 3 discusses the research design, data, measurement of variables, and methodology, including a discussion of model specification and estimation. Section 4 discusses our empirical findings while section 5 provides some validation and additional tests. Section 6 concludes the paper.

2. INSTITUTIONAL BACKGROUND AND HYPOTHESES

2.1. Inside the "Black Box" of Sell-side Analysts

Sell-side financial analysts are an important information intermediary in capital markets (Womack 1996; Jegadeesh et al. 2004; Ramnath et al. 2008; Da et al. 2011). A large literature has devoted to understanding the *consequences* of analyst coverages and identified two prominent roles of analysts: the interpretation of existing public information and discovery of new private information (e.g., Ivković and Jegadeesh 2004; Asquith et al. 2005; Chen et al. 2010). Early research largely focused on the information interpretation role of analysts and how they analyze and disseminate public, firm-specific information to investors (Francis et al. 2002; Pollock and Rindova 2003; Frankel et al. 2006; Tetlock 2007; Da et al. 2011). As sophisticated information intermediaries, analysts can collect and piece together information from various public sources such as SEC filings (e.g. form 10K, 8K etc.), corporate proxy statements, financial reports, etc. In a similar vein, Livnat and Zhang (2012) also provide evidence consistent with analysts' role as interpreters.[5] In addition to the traditional role as information interpreter, recent evidence suggests that

[5] Lo (2012) in his discussion, raises some concerns as to whether the results in Livnat and Zhang (2012) are robust.

analysts are capable of searching and discovering new information not yet publicly available. Consistent with this information discovery role, Ivković and Jegadeesh (2004) and Chen et al. (2010) provide evidence that analyst reports tend to pre-empt subsequent corporate disclosure, by releasing private information to capital markets. Overall, the literature supports that analysts can facilitate information flows and reduce information asymmetries facing investors, thereby contributing to the well-functioning of financial markets.

Although the literature has made considerable progress in exploring the *consequences* of analysts' research in capital markets, we have limited understanding of the *determinants* of analysts' research quality. Even though some studies began to explore the factors influencing analysts' coverage decisions (e.g., Barth et al. 2001), how analysts collect information and conduct private research about the covered firms remains largely a "black box" (Brown et al. 2015). One notable exception is Green et al. (2014), which finds that analysts attending corporate conference calls produce higher quality private research.

The objective of our study is to examine whether analysts actively learn from local media when conducting private research about covered firms. If so, what do they learn, and when analysts can benefit most from media news. The examination of the interplay between the local news media and financial analysts allows us to provide new insights into how differing sources of information interact to shape the information flow in capital markets. Given the important roles of financial analysts and news media in financial markets, understanding how analysts utilize information from the media can also advance our understanding of how different information intermediaries can complement each other in enhancing the quantity and quality of firm information available to investors and other market participants.[6]

2.2. Timeliness and Accuracy of Media News

The media has distinctive incentives and characteristics from analysts. Several unique features of news media make it a potentially important source for analysts to gain timely, credible insights when conducting private research about covered firms. First, news stories in the business press are likely to be timelier than analysts' reports. Based on the survey evidence of 475 financial journalists, Call et al. (2022)

[6] To the best of our knowledge, there are a few exceptions: e.g., Bushee et al. (2010) who examine news coverage of firms during earnings announcement and more recently Bradshaw et al. (2021).

find that almost 50% of the surveyed journalists report that their ability to gain access to senior management of companies is very important to help them develop timely articles about the covered firms. The timeliness of media news is consistent with prior empirical evidence suggesting that journalists seek to provide *original* information and analysis to readers (Miller 2006) and help motivate additional research on the mechanisms through which financial journalism influences financial markets (Guest 2021). Taking advantage of timely news articles about covered firms or exclusive insights of controversial topics, analysts can repackage and re-transmit available information from corporate disclosure and business press news stories in presenting in-depth analysis in their own reports (Lang and Lundholm 1996; Frankel et al. 2006).

Second, the content of news stories reported by financial journalists is likely more credible and subject to less biases compared to analysts' research. Unlike analysts whose compensation is tied to trading commission and investment-banking contribution (Groysberg et al. 2011), financial journalists are primarily evaluated based on accuracy, timeliness, and depth of news articles (Call et al. 2022). In particular, accuracy of the news article is assigned the highest weight when it comes to evaluating the quality of journalists' performance (Call et al. 2022).[7] The differing incentives of news media and analysts can shade differentially the contents of their disclosures or reports. While analysts can have strong incentives to optimistically skew disclosures or bias forecasts upwards to promote trading and commissions, financial journalists' incentives to be optimistic in their reports are muted.

2.3. Do Sell-side Analysts Learn from News Media?

The timeliness and accuracy of media news makes it a reliable, low-cost source for analysts to gain early and exclusive insights about covered firms. News media coverage could potentially facilitate analysts' research production via complementarities (Goldstein and Yang 2015). For one, analysts can learn early, exclusive insights of corporate news from local media. This is particularly important Post Reg-FD, which largely restricts analysts' direct access to senior management to gain private information. Even if analysts

[7] The accuracy and credibility of news articles reported by financial journalists is also consistent with empirical evidence on the monitoring role of the media in detecting corporate fraud and hold management accountable for misconduct (e.g., Miller 2006).

already possess a similar piece of firm information, in-depth news stories reported by financial journalists can help facilitate analysts' interpretation of the common news content if the news provide additional localized analysis or insider insights about covered firms. Such news content is likely to provide contextual information that may complement analysts' interpretation of the available news (Banker et al. 1993). [8] Furthermore, to the extent analysts are both disseminators and producers of information, they would benefit from an additional human source of analysis by the news media (and not technological source such as robo-journalism). More specifically, media articles often provide their assessment of the associated 'sentiment' of the news (Tetlock 2007), which may be valuable to analysts.

Although our argument predicts that analysts can learn and benefit from media news about covered firms, there are also plausible reasons that we may not find the predicted effect. For one, analysts have different objective functions. They may purposely bias their forecasts upward to cater for managers or generate more trading commissions (Francis and Philbrick 1993; Darrough and Russell 2002; Richardson et al. 2004). Second, analysts and news media share access to publicly available firm information disseminated via news wire (e.g. Business Wire, Market Wire, PR Newswire, and Global Newswire) or conference calls.[9] Given that both sources are factual and relatively precise, this would suggest that the information produced by analysts and the news media can be substitutes, thus leaving little or no room for either to learn from one another. Additionally, while Reg FD has restricted analysts access to corporate managers private information, there is still evidence that analysts may continue to have some private conversations with management in the "backroom chats." [10] It is also likely that new stories reported by the media is merely "attention grabbing" without providing much useful, incremental information to financial markets (e.g., Barber and Odean 2007; Fang et al. 2014).

[8] To the extent financial journalists behave like investors who as per evidence in Dyer (2021) use public information to enhance their local information advantage, one can expect them to provide a local flavor to their news reporting which may have valuable information content.
[9] We note that Li et al. (2023) document that newswires are more likely to send alerts on firms that have litigation exposure, report losses, included in major market indices and the like, suggesting some selective reporting.
[10] Green et al. (2014) suggest that access to management continues to be an important source of analysts' information advantage even in the post-Reg-FD period.

Overall, *ex ante*, it is not clear whether analysts research output benefits from the local news media and hence remains an important empirical question. In this study, we exploit the staggered county-level closure of local newspapers as an exogenous shock to firms' news coverage and examine whether the unexpected loss of news coverage of a firm adversely affects its analysts' research quality.

3. Research Design and Identification Strategy

3.1. Empirical Methodology: Plausibly Exogenous Shocks to Firms' News Coverage

Since both analyst and media coverage is unlikely to be random, an OLS regression that examines the association between the news coverage of a firm and its analysts' research production is subject to endogeneity concerns. To enhance our ability to draw causal inferences, we follow existing the literature (e.g., Gentzkow et al. 2011; Gao et al. 2020; Heese et al. 2022) and exploit staggered local newspaper closures in the U.S. as plausibly exogenous shocks to a firm's media coverage, and examine whether the reduction of the firm's news coverage due to such closures affects the informativeness of analysts' research outputs. These local newspaper closures provide an ideal setting to evaluate our research questions for two major reasons. First, the staggered county-level newspaper closures are unanticipated by firms and their analysts, therefore can address a host of endogeneity concerns related to reverse causality or omitted variables. Second, since an analyst typically follows multiple firms, the local newspaper shocks may affect one firm, but not all the firms covered by the analyst at a given time point. Thus, we can hold the analysts' unobservable characteristics constant and compare the analysts' research quality between firms affected by the newspaper closures (treatment) and those unaffected by such closures (control) firms followed by the same analyst.

To conduct this analysis, we construct a list of newspaper closures during our sample period using three data sources. The first source is the United States Newspaper Panel, constructed by Gentzkow et al. (2011). This database includes information on U.S. daily newspapers every four years from 1872 to 2004. Second, we obtain the closure events from 2006-2015 from Gao et al. (2020), which manually collect information on newspaper closures from the Editor and Publisher Yearbook.

Lastly, we expand the datasets to 2020 and supplement the closure events using UNC's center for innovation and sustainability in Local Media' Database of newspapers, which contains the name and geographical location of all daily and weekly newspapers in the U.S. We identify daily newspapers that disappear across the years and manually search for the year of the identified closures. We then match newspapers to our sample firms based on the location of the firms' headquarters. Following Gao et al. [2020], we match newspapers located on the border of two counties to both counties (Gao et al. 2020).

The combined dataset contains the name, city, and state of every daily newspaper in each of our sample years from 1972 to 2020. Similar to the methodology in Gentzkow et al. (2011), a county experiences a newspaper closure in year *t* if there is a reduction in the number of newspapers from year *t* to year *t* + 1. Using this methodology, we identify 286 newspaper closures.[11] Figure 1 reports the yearly distribution of closure events. We merge the county-year level closure dataset with our sample firms (see construction in section 3.3) based on their geographical location and zip code.

Consistent with the literature (e.g., Gentzkow et al. 2011; Gao et al. 2020; Heese et al. 2022), we define our treatment firms as firms that experienced U.S. daily local newspaper closures.[12] Our control firms are those whose locations are not affected by a newspaper closure during our sample period. If local newspapers provide an important source of information for analysts when conducting their private research, we expect that the closure of local newspapers should lead to a decline in research quality of analysts who follow the treatment firms. Our identification, therefore, exploits the changes in analysts' research in treatment firms after a newspaper closure compared to concurrent changes in the quality of analysts' research in control firms.

Specifically, we estimate the following difference-in-differences model:

[11] Our number of closure events is comparable to Gao et al. (2020), which report 216 newspaper closures for the period 1996 to 2015.
[12] Consistent with the literature, we do not consider mergers, changes in publication frequency (from daily to weekly), or changes to online because these events do not necessarily reduce local-news availability (Heese et al. 2022).

$$\textit{Informativeness of Analyst Research}_{ijt} = \alpha + \boldsymbol{\beta_1 Newspaper\ Closure_{ijt}} + \sum \beta_j\ Controls_{ijt} + \sum Firm\ x\ Analyst + \sum State\ x\ Year + \varepsilon \quad (1)$$

Where I, j, t denotes for analyst i covering firm j in year t. *Newspaper Closure* is an indicator variable that equals one for firm years after the closure of a local newspaper for a treatment firm, and zero otherwise. *Informativeness of Analyst Research* is measured by four different proxies, including analysts' forecast frequency, forecast timeliness, forecast accuracy, and price impact of analysts' revision. Please see section 3.2. for a detailed description of each variable.

Controls is a vector of control variables that potentially influences the informativeness of analyst research. Following the literature (e.g., Green et al. 2014), we include analyst-, brokerage- and firm-level controls. Specifically, we control for analyst experience by including the total number of firms she covers (FIRM_COVERAGE), the number of years she has been working as an analyst (ANALYST_EXPERIENCE) and the number of years she has followed the firm (FIRM_EXPERIENCE). We also include brokerage size (BROKER_SIZE) to control for the analyst's access to brokerage resource (Clement 1999). Further, we control for a firm's total analyst coverage (ANALYST_COVERAGE) to control for its overall information environment. Lastly, we include a set of firm-level fundamentals to control for time-varying cross-firm heterogeneity, including firm size (SIZE), profitability (ROA and Profitability), research and development (R&D), tangibility (TANG), internal cash flows (CASH), capital structure (LEV), growth opportunity (MTB), and dividend payout (DIVDUM).

We adopt a dense fixed effect structure to control for a host of potentially correlated, omitted variables. In all regressions, we include *firm-analyst* pair fixed effect, along with *state-year* and *year* fixed effects. The inclusion of firm-analyst pair fixed effects allows us to mitigate the concern that our results may be driven by firm and analyst matching. To isolate the impact of county-level newspaper closures, we also control for time varying state-level shocks (e.g., the adoption of state-level regulations). We also control for year fixed effect to eliminate the impact of time trends.

Our identification strategy therefore exclusively exploits the changes in the informativeness of analysts' research within each treatment firm-analyst pair, relative to those changes in control firm-analyst pairs. This is important given that one analyst can cover multiple firms, with some firms affected by newspaper closures and others not. Therefore, this setting allows us to compare the research outputs of the same analyst regarding different firms, pre and post the closure events, providing a powerful setting to identify the causal impact of local media on informativeness of analysts' research. If the closure of local newspapers reduces the informativeness of analysts' research, we expect β_1, the coefficient estimates on 'Newspaper closure' in equation (1) above, to be negative.

3.2. Informativeness of Analyst Research

Given the multifaceted nature of analyst outputs, we use five proxies to capture the informativeness of analysts' research based on their forecasts and revisions. The first three proxies capture analysts' forecast properties, including analyst forecast frequency, forecast timeliness, and forecast accuracy. The next two proxies are market-based, capturing price reaction to analyst forecast revision or recommendation changes. These measures capture different dimensions of analyst research, but all share a similar construct of the private information of analysts. We describe the details of construction of each variable below.

Analyst Forecast Frequency

Our first measure is analyst forecast frequency, based on the number of forecasts issued by an analyst for a company in any given year. Researchers find forecast frequency is associated with informativeness of analyst research. For example, Stickel (1992) find that all-American analysts forecast more frequently, and their forecast revision also have a greater price impact than non-all-Americans. We calculate analyst forecast frequency as the natural log of number of earnings forecasts issued by analyst i for firm j in year t.

Analyst Forecast Timeliness

Our second measure of analyst research informativeness is based on the timeliness of analyst earnings forecasts. Several studies argue that forecast timeliness is an effective measure of analysts' unobservable information advantage. For Example, Cooper et al. (2001) find a stronger relation between forecast timeliness and price impact than forecast accuracy and price impact. Jackson (2005) similarly shows that forecast timeliness is an important determinant of analyst all-star rankings.

Following prior research (e.g., Cooper et al. 2001), we use Leader-Follower Ratio (LFR) to capture the timeliness of analyst forecasts. LFR is calculated as the ratio of the cumulative number of days by which analyst I's forecast of firm j lags the prior two forecasts to the cumulative number of days by which the same forecast leads the next two forecasts (excluding forecasts by the same analysts). This ratio captures the intuition that the forecast of a skilled or informed analyst is more likely to induce forecasts by other analysts than vice versa.

Analyst Forecast Accuracy

Our third measure is the relative accuracy of analysts' earnings forecasts. Consistent with the literature (e.g., Green et al. 2014), we calculate analyst forecast accuracy (ACCURACY) as the negative value of PMAFE, where PMAFE is the proportional mean forecast accuracy introduced by (Clement 1999). One advantage of using relative measure of analyst forecast accuracy is that it can better capture the unobservable information advantage of analyst, relative to her/his peers. Consistent with the literature, we eliminate all analyst forecasts issued within five days of a quarterly earnings announcement (Cooper et al. 2001). We then calculate analyst forecast accuracy using the equation below:

$$Accuracy = (-1) * PMAFE = (-1) * (AFE_{ijt} - \overline{AFE_{jt}}) / \overline{AFE_{jt}}$$

Where AFE_{ijt} is the absolute forecast error for analyst I's forecast of firm j for year t earnings, and $\overline{AFE_{jt}}$ is the mean absolute forecast error for firm j in year t. We multiplied PMAFE by one hundred so that the forecast errors are expressed in percentage term. Lastly, we multiply PMAFE by negative one so that higher values indicate greater forecast accuracy.

Price Reaction to Analyst Forecast Revision and Stock Recommendation Changes

In addition to analysts' forecasts, the literature also uses price reaction to analyst forecast revision or stock recommendation changes to capture the informativeness of analyst research. (e.g., Loh and Stulz

2010; Green et al. 2014). Following the literature, we measure the informativeness of analysts' research as the stock-price reaction in the two-day event window [0,1] where day 1 is the announcement date of the forecast revision or stock recommendation changes. We compute the two-day buy-and-hold cumulative abnormal return (CAR) following the research report as:

$$CAR = \prod_{t=0}^{1}(1 + R_{it}) - \prod_{t=0}^{1}(1 + R_{it}^{DGTW})$$

Where R_{it} is the raw return of stock I on day t, and R_{it}^{DGTW} is the return on day t of a benchmark portfolio with the same size, book-to-market, and momentum characteristics as the stock. Higher values of market reaction to analyst forecast revisions or stock recommendation changes indicate more informativeness of analyst research.

3.3. Sample, Data and Descriptive Statistics

We construct our sample using public data from several sources: (1) media coverage and sentiment data from RavenPack, (2) firm-level financial data from Compustat, and (3) analyst forecast data from the Institutional Brokers' Estimate System (I/B/E/S) detail file, and (4) stock price data from CRSP database. Our baseline sample is the intersection of Compustat and I/B/E/S database. We obtain data on individual analysts' earnings forecasts from I/B/E/S detail History data set. We remove analysts coded as anonymous by I/B/E/S because it is not possible to track their forecast changes. Consistent with Loh and Stulz (2010), we exclude forecast revisions that fall in the three-day window around quarterly earnings announcements. We then merge our sample firms with the constructed list of local newspaper closure events based on their geographical location and zip code. Our final sample for analyst forecast-related analyses consists of 120,472 firm-analyst-year observations during the period 2001 to 2020. Our sample size for a specific test may vary depending on the data requirements.

Table 1 reports the descriptive statistics of regression variables. We report the statistics for treatment and control firms separately. As shown, we find the treatment and control firms are comparable in terms of analysts' forecast property. The mean value of frequency is 5.85 for treatment firms, whereas it is 5.92 for control firms. The accuracy of analysts' forecasts is also similar, with -2.32 for treatment firms, and -2.47 for control firms. Our treatment and control firms are also comparable in terms of firm size (SIZE), profitability (ROA) and growth opportunities (MTB). These statistics suggest that our results are unlikely driven by observable differences between treatment and control firms prior to the closure events.

[Insert Table 1]

4. Empirical Results

4.1. Newspaper Closures and Analysts' Forecast Frequency

Table 2 reports the results on analysts' forecast frequency. Column (1) reports the results of specification including firm and state-year fixed effects. As shown, we find that local newspaper closures lead to a significant decline in the frequency of earnings forecasts for analysts who followed the treatment firms (p-value<0.01). our result continues to hold in column (2) when we include firm-analyst pair fixed effects. Taking the coefficient in column (2) as the example, analysts covering treatment firms are issue 1.05 less earnings forecast after newspaper closures. [13] It should be noted that our results hold after controlling for analyst experiences, brokerage resource and total analyst coverage of firms, and a wide range of firm-level fundamentals. The incremental impact of newspaper closure on analysts' forecast frequency is consistent with local newspapers providing useful information to analysts when issuing forecasts for treatment firms.

[Insert Table 2]

4.2. Newspaper Closures and Analysts' Forecast Timeliness

Table 3 reports the results of local newspaper closures on analysts' forecast timeliness. We report the results under a similar tables structure as in Table 2. In both columns (1) and (2), we document a decline in the timeliness of analysts' forecasts using the leader-follower ratio (LFR), another proxy for analysts' private information (Cooper et al. 2001; Green et al. 2014). The coefficient on *Closure* is negative and significant (p-value<0.01), suggesting that local newspaper closures lead to a decrease in analysts' forecast

[13] The coefficient on Closure is -0.051, the magnitude of decrease in earnings forecast is exp (0.051) =1.05.

timeliness. The impact is also economically significant. For example, the coefficient on Closure in column (2) is -0.271, suggesting that the closure of local newspaper leads to a 265 basis-point decrease in analysts forecast timeliness, which is equivalent to 6% of its mean.[14] These results again support the argument that local newspapers serve an important source for analysts to gain relevant information about covered firms and incorporate that information in issuing forecasts.

[Insert Table 3]

4.3. Newspaper Closures and Analysts' Forecast Accuracy

In Table 4, we further investigate the consequence of local newspaper closures on analysts' forecast accuracy. If analysts do incorporate information from local newspapers, the closure of newspapers will lead to a decline in their forecast accuracy in treatment firms relative to that of a control sample of firms unaffected by the closures. We find consistent evidence in both columns (1) and (2). Taking the coefficient in column (2) as an example, the newspaper closures lead to a 701 basis-point decrease in analysts' forecast accuracy, which is equivalent to 12.92% of its mean value. This result, corroborating with our prior findings, suggest that analysts produce less accurate forecasts for firms experiencing an adverse shock to their news coverage, compared to other firms covered by the same analysts but did not experience a reduction in news coverage by local media.

[Insert Table 4]

4.4. Newspaper Closures and Informativeness of Analysts' Forecast Revision

Table 5 reports our main results of estimating model (1) using two-day CAR of analyst forecast revision as the dependent variable. Forecast revisions are computed as the current forecast for one-year ahead earnings minus the prior forecast issued by the same analyst and are widely used as a comprehensive measure for analyst research informativeness (e.g., Frankel et al. 2006; Green et al. 2014). Consistent with Loh and Stulz (2010), we exclude forecast revisions that fall in the three-day window around quarterly

[14] The magnitude of economic significance is comparable with those reported in the literature. For example, (Green et al. 2014) examine whether analysts with conference access to management can issue more informative forecasts. They find that post-conference forecasts of hosts are 5.01% more accurate than non-host forecasts.

earnings announcements. As shown in Columns (1) and (2), we find that local newspaper closures lead to significantly weaker market reaction to analysts' forecast revisions. This result does not support that media news and analyst research are substitute information sources for investors. If information reported by the media and analysts serve as substitute for investors, the closure of local newspapers should result in a stronger, not weaker, market reaction to analyst revision. Our finding of a weaker market reaction to analysts' forecast revision is consistent with our argument that analysts do incorporate news reported by local media when conducting private research about the covered firms.

[Insert Table 5]

4.5. Newspaper Closures and Informativeness of Analysts' Stock Recommendation Changes

We also examine whether local newspaper closures also lead to less informative recommendation changes of analysts issued about the treated firms. We obtain data on stock recommendations from I/B/E/S database, which contains the recommendation of individual analysts with ratings ranging from 1(strong buy) to 5 (strong sell). Consistent with Green et al. (2014), we calculate recommendation changes as the current rating minus the prior rating by the same analyst. We similarly exclude recommendations that fall in the three-day window around quarterly earnings announcement dates (obtained from Compustat). We then calculate the two-day buy-and-hold cumulative abnormal return (CAR) around the dates of recommendation changes as detailed in Section 3.2.

Table 6 reports the results of this analysis. We find consistent results that local newspaper closures lead to a significant decline in the informativeness of analyst stock recommendation for the treatment firms. The coefficient on *Newspaper Closure* is negative and significant (p-value<0.05). In all regressions, we control for the magnitude of changes in stock recommendations. Thus, any incremental effect of *Newspaper Closures* on market reaction to analysts' recommendation changes (*CAR_RECOMM*) should be attributed to the incremental information content associated with local newspapers.

[Insert Table 6]

In summary, our results in Table 2-6 establish the learning of analysts from the media: local newspapers provide an important source for analysts to gain firm-relevant information when conducting private research. The staggered and plausibly exogenous nature of newspaper closure largely alleviates the concerns of endogeneity. The consistency and robustness of our results using all four analyst measures suggest that our results are unlikely driven by the measurement choice of analyst research informativeness.

4.6. What do Analysts Learn from the Media? News Content, Sentiment and Subcategories

Establishing the learning effect, we next deepen our analysis to explore what analysts learn from the media. Specifically, we exploit cross-sectional variation conditional on *News Content, Media Sentiment and News Subcategories*. To capture the changes in the total amount of private information possessed by analysts, we follow prior research (e.g., Green et al. 2014), and focus on price reaction to analysts' forecast revision (CAR) as the summary measure for analyst research quality in our cross-sectional analyses.[15] We report the results of these analyses in Table 7.

Table 7, Panel A reports the cross-sectional results conditional on news content and news sentiment. Research suggests that the initial news coverage of a firm conveys more new information than repetitive news coverage (e.g., Dai et al. 2015). Therefore, we examine whether the impact of newspaper closures on analyst research is driven by the initial coverage of the news for a treatment firm (*FIRST_NEWS*) prior to the shock. As shown in column (1), we find that the decline in CAR around analysts' revision is more pronounced when treatment firms receive the first news coverage prior to the closure.

In addition to news coverage, we also expect the impact of the media on analysts to vary depending on the media sentiment when conveying the firm news. Research shows that the tone of news articles can affect public attention and predict stock market movement (Tetlock 2007). We use Event Sentiment Scores (ESS) to capture media sentiment, RavenPack detects and categorizes the news. It creates a news sentiment score between 0 and 100 for each news article based on proprietary algorithms. It is determined by systematically matching stories with a short-term positive or negative financial or economic impact. To

[15] Our results remain inferentially unchanged if we conduct cross-sectional analyses using a composite measure of analyst research informativeness. As an additional analysis (untabulated), we construct a composite measure of analyst research informativeness based on the average percentile rankings of each informativeness measures: analyst forecast frequency, analyst forecast timeliness, analyst forecast accuracy and price reaction to analyst revision. We find consistent results.

facilitate our empirical analysis, we scale the media sentiment score by 100 and consider the score greater (below) than 0.5 as a positive (negative) event. As reported in Column (2), we find that the impact of media news on analysts' research is driven by news with negative tones, consistent with Tetlock (2007) that negative sentiment predicts stock market pessimism.

In Table 7, Panel B, we examine whether the impact of the media news on analysts' research varies depending on the 'type' of news. To conduct this analysis, we follow a recent study by Jeon et al. (2022) and retrieve detailed news coverage data for each treatment firm from Ravenpack database. Ravenpack categorize the news into several groups, including earnings and revenues, analyst ratings, capital structure, Mergers and Acquisitions (M&As), marketing and investor relations, labor issues and executive turnovers and products and services information, insider trading and legal issues. We then partition our sample firms based on the pre-closure news coverage in each category and identify high-news coverage firms with news coverage in corresponding category above the sample median. The results reported in Table 7 suggest that the post-closure decline in analysts' research informativeness is driven by the loss of negative news about local firms' earnings and legal proceedings associated with the newspaper closures.

[Insert Table 7]

4.7. Which Analysts Benefit More from the Media: Analyst Uncertainty, Capability and Resource Constraint

In this section, we further explore what type of analysts benefit from more local media. To this end, we exploit variation in analysts' information uncertainty, capability, and resource constraints. Table 8 reports the results of these analyses. Panel A reports the results conditional on analysts' information uncertainty. We use a firm's complexity and reporting opacity to capture the extent of information uncertainty facing analysts. Research suggests that information environments for complex firms (e.g., firms operating across multiple segments) are typically opaquer and more difficult to predict (e.g., Chen et al. 2018). We also use a composite measure of financial reporting opacity to capture information uncertainty, based on absolute abnormal accruals, small loss avoidance and income smoothing (Leuz et al. 2003). In columns (1) and (2), we find that local newspapers play a larger role when analysts cover more complex firms with opaque financial reporting: the treatment effect of newspaper closure on analysts' research is significantly stronger when treatment firms are those complex, and opaque firms.

Panel B reports the results conditional on analysts' capability and resource constraints. We capture an analyst's capability based on the number of years the analyst has been following a given firm. We expect that the longer an analyst has been following a firm, the more experienced this analyst is in issuing forecasts related to this firm. We also capture analysts' resource support based on the size of their affiliated brokerages as prior research indicates that brokerage size is an important determinant of analysts' resource support (Clement 1999). We expect that analysts with less experience covering a firm while facing greater resources constraints are more likely to benefit from local news of the firm reported by the media. We find consistent evidence in Columns (1) and (2). The post-closure decline in analysts' research informativeness is more pronounced for less experienced analysts and analysts from smaller brokerages, such that the marginal benefits of media news are likely larger.

[Insert Table 8]

Collectively, our results in Tables 7 and 8 reinforce our main findings and provide further insights into when and what types of news matter most in analysts' research. Our findings suggest that analysts do incorporate media news about the covered firm in their private research. The informational benefit of media news is larger when the news is about firms' earnings or legal proceedings or when the tone of the news is negative. Analysts also benefit more from local news when they face higher uncertainty, have less experience with the covered firms and face higher resource constraints.

5. Additional Analyses and Robustness Tests

5.1. Robustness Test: OLS regression using RavenPack Data

Our main identification exploits staggered county-level local newspaper closures as plausibly exogenous shocks to firms' news coverage and examines their subsequent impact on analysts' research production. As an additional analysis, we also conduct an OLS regression analysis using detailed news coverage data reported by RavenPack. We obtain data on news coverage from RavenPack, a leading global news database of stories published about companies listed on the NYSE, AMEX, and NASDAQ.

RavenPack has been widely used in academic studies (e.g., Kolasinski and Li 2013; Shroff et al. 2014; Dai et al. 2015; Dang et al. 2015).

RavenPack classifies news articles into different categories using proprietary text and part-of-speech tagging or labeling. To ensure the news is firm-relevant, we set the news-relevance score (NRS) to 100 to restrict the news to firm-focused news. To avoid potential endogeneity (e.g., Cui and Docherty 2020) we exclude "analyst-related" news. We then aggregate the number of news articles at the firm-year level to capture the frequency of news flows covering a given firm. We use Event Sentiment Scores (ESS) to capture media sentiment, RavenPack creates a news sentiment score between 0 and 100 for each news article based on proprietary algorithms. It is determined by systematically matching stories with a short-term positive or negative financial or economic impact. To facilitate our empirical analysis, we scale the media sentiment score by 100 and consider the score greater (below) than 0.5 as a positive (negative) event.

To examine the impact of frequency of news flow and tone of the news on analysts' research, we estimate the following fixed effect OLS regression:

$$Informativeness\ of\ Analyst\ Research_{it} = \alpha + \beta_{1} NewsCount_{it} + \beta_{2} |NewsTone|_{it} + \beta_{j} \sum Controls_{it} + \sum Firm + \sum Year + \varepsilon, \quad (2)$$

Where *Informativeness of Analyst Research* is measured by analysts' forecast accuracy (*ACCURACY*) or three-day abnormal return (*CAR*) around analyst forecast revision. *NewCount* is the natural log of number of news articles covering firm I in year t. $|NewsTone|$ is the absolute value of news sentiment score reported by Ravenpack. We include the same set of control variables as in model (1). We include firm-analyst and year fixed effects in all regressions to absorb firm-analyst pair fixed effect and time trends. To be consistent with H1, we expect β_{1} and β_{2} to be positive, suggesting that the frequency of news flow and tone of the news help increase the informativeness of analysts' research.

5.2. OLS regression Results on Analysts' Forecast Accuracy

Table 9 reports the results of estimating model (1) using analysts' forecast accuracy as the dependent variable. One benefit of using analysts' forecast accuracy is that the measure is constructed by comparing one analyst's forecast accuracy for a given firm with those of her peers covering firms within the same industry. Therefore, this measure allows us to better identify whether greater news coverage of a firm enables the analyst to produce more accurate forecasts, relative to her peers covering other firms within the same industry. Column (1) shows that both news count and news tone are positively associated with analysts' forecast accuracy. When we further separate the forecasts based on the direction of forecast errors, we find that news tones mainly reduce forecast errors with upward biases, and news coverage mainly reduces forecast errors with downward biases.

[Insert Table 9]

5.3. OLS Regression Results on Informativeness of Analysts' Revisions

Table 10 reports the OLS results on informativeness of analysts' revisions (CAR). Column (1) shows that both the frequency of the news flow and the tone of the news are positively associated with *CAR*. This result is consistent with our argument that the media news serves as an important source for analysts to obtain private information and enhance the informativeness of analyst research.

When we further separate analysts' revisions into upgrades and downgrade revisions in columns (2) and (3), we find that the impact of news count and news tone are more pronounced when analysts generate downgrade revisions. These results are consistent the notion that media news helps reduce analysts optimism, and Tetlock (2007) that higher media pessimism predicts downward pressure on market prices. Overall, the OLS regressions result in Tables 9 and 10 reinforce our main findings and suggest that both the frequency of news flows and tone of the news can explain the informativeness of analyst research.

[Insert Table 10]

6. Conclusion

Research has documented the role of financial analysts and business press as two independent information intermediaries that facilitate the dissemination of information in financial markets (e.g., Bushee et al. 2010; Drake et al. 2014; Blankespoor et al. 2018). However, we still lack a complete understanding of whether the two intermediaries learn and benefit from each other and how their interactions shape the information flows in capital markets. In this paper, we examine whether analysts actively incorporate news stories reported by local media when conducting private research, and if so, what they learn and the extent to which the learning affects their research quality. Our empirical design exploits staggered county-level local newspaper closures as plausible exogenous shock to firms' news coverage and examines its subsequent impact on research quality of analysts who follow the treatment firms. This design allows us to compare the research quality of treatment firms and those of control firms covered by the same analyst, holding analyst characteristics constant. Using a difference-in-differences design, we find that analysts do learn from local news media and incorporate relevant firm specific news to improve the quality of their private research. Our baseline results show that analysts produce less frequent, timely and accurate earnings forecasts when their covered firms lose media coverage after these shocks. The market also reacts less strongly to analysts' forecast revisions and stock recommendation changes. Our findings hold after controlling for firm, firm-analyst, and year fixed effects, suggesting that our findings are unlikely attributed to constant observable firm characteristics, firm-analyst matching, or time trends.

Additionally, we document that the improvement in analyst research is driven by a reduction in analyst optimism. Newspaper closures have a greater impact on analysts when the local media initiates the first coverage of firms, reported negative news about firm earnings or legal proceedings. Analysts also tend to learn more from local news when they cover more complex, opaque firms, have less experience with the covered firm or are affiliated with smaller brokerages. These additional results not only reinforce our primary findings but also help delineate the settings where analysts can learn and benefit the most from firm news reported by the local media. Further analysis suggests that both the frequency of news flows and the tone of the news contribute to the informativeness of analysts' research. To the best of our knowledge, our study is the first to provide a more nuanced understanding of how analysts' research is influenced by the local news media. More fundamentally, we document an important interplay between the two primary intermediaries in the financial markets i.e., analysts and news media.

REFERENCES

Asquith, P., M. B. Mikhail, and A. S. Au. 2005. Information content of equity analyst reports. *Journal of Financial Economics* 75 (2):245-282.

Banker, R. D., S. Das, and S. M. Datar. 1993. Complementarity of prior accounting information: The case of stock dividend announcements. *Accounting review*:28-47.

Barber, B., R. Lehavy, and B. Trueman. 2004. Comparing the Stock Recommendations Performance of Investment Banks and Independent Research: working paper.

Barber, B. M., and T. Odean. 2007. All That Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors. *The Review of Financial Studies* 21 (2):785-818.

Barth, M. E., R. Kasznik, and M. F. McNichols. 2001. Analyst coverage and intangible assets. *Journal of Accounting Research* 39 (1):1-34.

Blankespoor, E., E. deHaan, and C. Zhu. 2018. Capital market effects of media synthesis and dissemination: evidence from robo-journalism. *Review of Accounting Studies* 23 (1):1-36.

Bradshaw, M. T., T. E. Christensen, K. H. Gee, and B. C. Whipple. 2018. Analysts' GAAP earnings forecasts and their implications for accounting research. *Journal of Accounting and Economics* 66 (1):46-66.

Bradshaw, M. T., B. Lock, X. Wang, and D. Zhou. 2021. Soft information in the financial press and analyst revisions. *The Accounting Review* 96 (5):107-132.

Brown, L. D., A. C. Call, M. B. Clement, and N. Y. Sharp. 2015. Inside the "black box" of sell‐side financial analysts. *Journal of Accounting Research* 53 (1):1-47.

Bushee, B. J., J. E. Core, W. Guay, and S. J. Hamm. 2010. The role of the business press as an information intermediary. *Journal of Accounting Research* 48 (1):1-19.

Bushee, B. J., D. A. Matsumoto, and G. S. Miller. 2004. Managerial and investor responses to disclosure regulation: The case of Reg FD and conference calls. *The Accounting Review* 79 (3):617-643.

Call, A. C., S. A. Emett, E. Maksymov, and N. Y. Sharp. 2022. Meet the press: Survey evidence on financial journalists as information intermediaries. *Journal of Accounting and Economics* 73 (2-3):101455.

Chen, C., X. Martin, S. Roychowdhury, X. Wang, and M. T. Billett. 2018. Clarity Begins at Home: Internal Information Asymmetry and External Communication Quality. *The Accounting Review* 93 (1):71-101.

Chen, X., Q. Cheng, and K. Lo. 2010. On the relationship between analyst reports and corporate disclosures: Exploring the roles of information discovery and interpretation. *Journal of Accounting and Economics* 49 (3):206-226.

Clement, M. B. 1999. Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter? *Journal of Accounting and Economics* 27 (3):285-303.

Cooper, R. A., T. E. Day, and C. M. Lewis. 2001. Following the leader:: a study of individual analysts' earnings forecasts. *Journal of Financial Economics* 61 (3):383-416.

Cui, B., and P. Docherty. 2020. Stock Price Overreaction to ESG Controversies, Working Paper. *Available at SSRN: https://ssrn.com/abstract=3559915 or http://dx.doi.org/10.2139/ssrn.3559915*.

Da, Z., J. Engelberg, and P. Gao. 2011. In search of attention. *The journal of finance* 66 (5):1461-1499.

Dai, L., J. T. Parwada, and B. Zhang. 2015. The governance effect of the media's news dissemination role: Evidence from insider trading. *Journal of Accounting Research* 53 (2):331-366.

Dang, T. L., F. Moshirian, and B. Zhang. 2015. Commonality in news around the world. *Journal of Financial Economics* 116 (1):82-110.

Darrough, M. N., and T. Russell. 2002. A positive model of earnings forecasts: Top down versus bottom up. *The Journal of Business* 75 (1):127-152.

Drake, M. S., N. M. Guest, and B. J. Twedt. 2014. The Media and Mispricing: The Role of the Business Press in the Pricing of Accounting Information. *The Accounting Review* 89 (5):1673-1701.

Dyer, T. A. 2021. The demand for public information by local and nonlocal investors: Evidence from investor-level data. *Journal of Accounting and Economics* 72 (1):101417.

Fang, L. H., J. Peress, and L. Zheng. 2014. Does Media Coverage of Stocks Affect Mutual Funds' Trading and Performance? *The Review of Financial Studies* 27 (12):3441-3466.

Francis, J., and D. Philbrick. 1993. Analysts' decisions as products of a multi-task environment. *Journal of Accounting Research* 31 (2):216-230.

Francis, J., K. Schipper, and L. Vincent. 2002. Earnings announcements and competing information. *Journal of Accounting and Economics* 33 (3):313-342.

Frankel, R., S. Kothari, and J. Weber. 2006. Determinants of the informativeness of analyst research. *Journal of Accounting and Economics* 41 (1-2):29-54.

Gao, P., C. Lee, and D. Murphy. 2020. Financing dies in darkness? The impact of newspaper closures on public finance. *Journal of Financial Economics* 135 (2):445-467.

Gentzkow, M., J. M. Shapiro, and M. Sinkinson. 2011. The effect of newspaper entry and exit on electoral politics. *American Economic Review* 101 (7):2980-3018.

Goldstein, I., and L. Yang. 2015. Information diversity and complementarities in trading and information acquisition. *The journal of finance* 70 (4):1723-1765.

Green, T. C., R. Jame, S. Markov, and M. Subasi. 2014. Access to management and the informativeness of analyst research. *Journal of Financial Economics* 114 (2):239-255.

Groysberg, B., P. M. Healy, and D. A. Maber. 2011. What drives sell-side analyst compensation at high-status investment banks? *Journal of Accounting Research* 49 (4):969-1000.

Guest, N. M. 2021. The information role of the media in earnings news. *Journal of Accounting Research* 59 (3):1021-1076.

Heese, J., G. Pérez-Cavazos, and C. D. Peter. 2022. When the local newspaper leaves town: The effects of local newspaper closures on corporate misconduct. *Journal of Financial Economics* 145 (2):445-463.

Ivković, Z., and N. Jegadeesh. 2004. The timing and value of forecast and recommendation revisions. *Journal of Financial Economics* 73 (3):433-463.

Jackson, A. R. 2005. Trade Generation, Reputation, and Sell-Side Analysts. *The journal of finance* 60 (2):673-717.

Jegadeesh, N., J. Kim, S. D. Krische, and C. M. Lee. 2004. Analyzing the analysts: When do recommendations add value? *The journal of finance* 59 (3):1083-1124.

Jeon, Y., T. H. McCurdy, and X. Zhao. 2022. News as sources of jumps in stock returns: Evidence from 21 million news articles for 9000 companies. *Journal of Financial Economics* 145 (2):1-17.

Kolasinski, A. C., and X. Li. 2013. Can Strong Boards and Trading Their Own Firm’s Stock Help CEOs Make Better Decisions? Evidence from Acquisitions by Overconfident CEOs. *Journal of Financial and Quantitative Analysis* 48 (4):1173-1206.

Kothari, S. P., X. Li, and J. E. Short. 2009. The effect of disclosures by management, analysts, and business press on cost of capital, return volatility, and analyst forecasts: A study using content analysis. *The Accounting Review* 84 (5):1639-1670.

Lang, M. H., and R. J. Lundholm. 1996. Corporate disclosure policy and analyst behavior. *Accounting review*:467-492.

Leuz, C., D. Nanda, and P. D. Wysocki. 2003. Earnings management and investor protection: an international comparison. *Journal of Financial Economics* 69 (3):505-527.

Li, E. X., G. Lind, K. Ramesh, and M. Shen. 2023. Externalities of accounting disclosures: evidence from the Federal Reserve. *The Accounting Review*:1-27.

Lin, H.-w., and M. F. McNichols. 1998. Underwriting relationships, analysts' earnings forecasts and investment recommendations. *Journal of Accounting and Economics* 25 (1):101-127.

Livnat, J., and Y. Zhang. 2012. Information interpretation or information discovery: Which role of analysts do investors value more? *Review of Accounting Studies* 17:612-641.

Loh, R. K., and R. M. Stulz. 2010. When Are Analyst Recommendation Changes Influential? *The Review of Financial Studies* 24 (2):593-627.

Miller, G. S. 2006. The press as a watchdog for accounting fraud. *Journal of Accounting Research* 44 (5):1001-1033.

Miller, G. S., and D. J. Skinner. 2015. The evolving disclosure landscape: How changes in technology, the media, and capital markets are affecting disclosure. *Journal of Accounting Research* 53 (2):221-239.

Pollock, T. G., and V. P. Rindova. 2003. Media legitimation effects in the market for initial public offerings. *Academy of Management journal* 46 (5):631-642.

Ramnath, S., S. Rock, and P. Shane. 2008. The financial analyst forecasting literature: A taxonomy with suggestions for further research. *International Journal of Forecasting* 24 (1):34-75.

Richardson, S., S. H. Teoh, and P. D. Wysocki. 2004. The walk‐down to beatable analyst forecasts: The role of equity issuance and insider trading incentives. *Contemporary accounting research* 21 (4):885-924.

Shroff, N., R. S. Verdi, and G. Yu. 2014. Information Environment and the Investment Decisions of Multinational Corporations. *The Accounting Review* 89 (2):759-790.

Stickel, S. E. 1992. Reputation and Performance Among Security Analysts. *The journal of finance* 47 (5):1811-1836.

Tetlock, P. C. 2007. Giving content to investor sentiment: The role of media in the stock market. *The journal of finance* 62 (3):1139-1168.

———. 2015. The role of media in finance. *Handbook of media Economics* 1:701-721.

Womack, K. L. 1996. Do brokerage analysts' recommendations have investment value? *The journal of finance* 51 (1):137-167.

Appendix A. Variable Descriptions

Variables	Description	Source
Informativeness of Analyst Research		
FREQ	Natural log of number of earnings forecasts issued by an analyst for a given firm and year	I/B/E/S
TIMELINESS	Leader-follower ratio, calculated as the number of days by which analyst I's forecast of firm j lags the prior two forecasts to the cumulative number of days by which the same forecast leads the next two forecasts (excluding forecasts by the same analyst)	I/B/E/S
ACCURACY	The proportional mean forecast accuracy defined as the absolute forecast error for analyst I's forecast of firm j for year t earnings less the mean absolute forecast error (all analysts for firm j in year t), scaled by the mean absolute forecast error (multiplied by 100)	I/B/E/S
CAR	Buy-and-hold abnormal returns calculated based on stock-price reaction in the two-day event window [0,1], where day 0 is the announcement date of the forecast revision	CRSP, I/B/E/S
CAR_RECOMM	Buy-and-hold abnormal returns calculated based on stock-price reaction in the two-day event window [0,1], where day 0 is the announcement date of the recommendation change	CRSP, I/B/E/S
Media News Coverage		
NewSpaper Closure	An indicator variable that equals one for firm-year observations in treatment firms (in countries with newspaper closures) after each newspaper closure event, and zero otherwise	Gao et al. (2015), UNC database
Information Content of Media		
NewsCount	Natural log of number of initial news articles with a relevance score of 100 for the firm, based on the news event categories according to the RavenPack taxonomy.	Ravenpack Database
|*NewsTone*|	The absolute value of sentiment score scaled from 0 to 1, based on ESS score reported by Ravenpack Database.	Ravenpack Database
Control Variables		
Controls of analyst experiences		
Firm_Coverage	Number of firms covered by analyst i in year t	I/B/E/S

Log (Analyst Experience)	Natural log of number of years since the analyst first issued earnings forecast (for any firm).	I/B/E/S
Log (Firm_Experience)	Natural log of number of years the analyst has covered the firm	I/B/E/S
Control of Brokerage resource		
Broker_Size	Total number of analysts working at the brokerage firm of the recommending analyst	I/B/E/S
Control of analyst coverage		
Analyst_Coverage	Total number of firms followed by an analyst in a given year	I/B/E/S
Controls of firm characteristics		
SIZE	Natural log of total book assets	Compustat database
ROA	Net income before extraordinary items and preferred dividends scaled by beginning total assets	Compustat database
RD	Total research and development expenditures scaled by total assets	Compustat database
TANG	Fixed assets ratio calculated as net property, plant, and equipment divided by book value of assets.	Compustat database
CASH	Cash flow from operations	Compustat database
LEV	Total liabilities/Market value of total assets	Compustat database
MTB	Market value of assets divided by book value of assets=(AT-BE+ME)/AT	Compustat database
DIVDUM	An indicator variable that equals one for firms reporting positive amounts of dividends for common stocks and zero otherwise	Compustat database
PROFIT	Ratio of earnings before interest, taxes, depreciation and amortization (EBITDA) divided by book value of assets.	Compustat database
Conditioning Variables		
Media Content, Tone and Types		
First News	An indicator variable that equals one if the initial news coverage of a firm exceeds the sample median prior to the shock, and zero otherwise.	Ravenpack Database
Negative News	An indicator variable that equals one if the negative news coverage of a firm exceeds sample median prior to the shock, and zero otherwise. The	Ravenpack Database

	event is categorized as negative (positive) event when the sentiment is below (above or equal to) 0.5.	
Earnings News	An indicator variable that equals one if the news coverage of a firm related to its "revenue" or "earnings" ("Group" as reported by Ranvenpack) exceeds the sample median prior to the shock, zero otherwise.	Ravenpack Database
Legal News	An indicator variable that equals one if the news coverage of a firm related to its "regulatory" or "legal" ("Group" as reported by Ranvenpack) exceeds the sample median prior to the shock, zero otherwise.	Ravenpack Database
Analyst Uncertainty, Capability and Resource Constraint		
Complex Firm	An indicator variable that equals one if a firm is multi-segment firms (with business segments greater than two), and zero otherwise	Compustat database
Opaque Firm	An indicator variable that equals one if a firm's financial reporting opacity exceeds the sample median prior to the shock, and zero otherwise. Opacity is calculated as average percentile rankings of magnitude of performance-adjusted discretionary accruals (Kothari et al. 2005), accrual quality (Dechow and Dechev 2002), and small loss avoidance (Burgstahler and Dichev 1997).	Compustat database
Less Experienced	An indicator variable that equals one if the number of years that an analyst covers a firm is less than the sample median, and zero otherwise.	I/B/E/S
Small Broker	An indicator variable that equals one if the size of the brokerage house that an analyst affiliated with is less than the sample median and zero otherwise	I/B/E/S

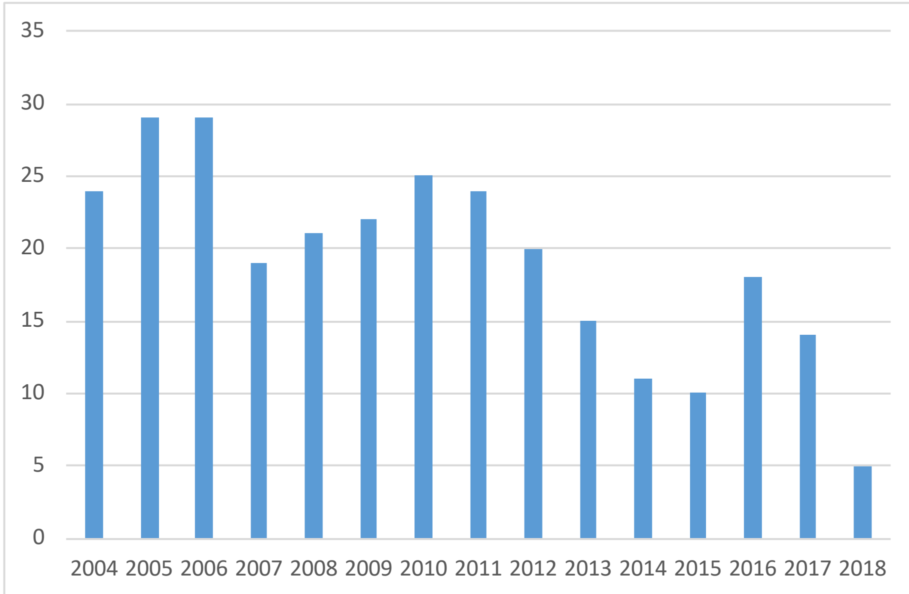

Figure 1. Number of newspaper closures per year. The graph displays the number of newspaper closures per year for the period 2004-2020

Table 1
Descriptive Statistics of Selected Regression Variables

	Treat=1				Treat=0			
Variable	**N**	**Mean**	**Median**	**Std Dev**	**N**	**Mean**	**Median**	**Std Dev**
Frequency	30587	5.849	5.935	0.925	89885	5.925	6.033	0.885
Accuracy	30587	-2.322	-0.936	5.425	89885	-2.471	-0.934	5.917
Timeliness	25246	4.441	1.000	12.164	83184	4.650	1.000	12.542
CAR_Rev	37826	0.016	0.008	0.056	132396	0.018	0.009	0.058
CAR_Recomm	13832	-0.004	-0.001	0.081	44174	-0.004	-0.001	0.078
Firm_Coverage	30587	2.829	2.890	0.548	89885	2.800	2.833	0.538
Log (Analyst Experience)	30587	2.321	2.565	0.886	89885	2.338	2.565	0.883
Log (Firm_Experience)	30587	1.268	1.386	0.912	89885	1.297	1.386	0.923
Broker_Size	30587	6.086	6.382	1.080	89885	6.105	6.410	1.078
Analyst_Coverage	30587	2.685	2.833	0.707	89885	2.737	2.890	0.689
SIZE	30587	7.598	7.710	2.028	89885	7.889	7.982	1.856
ROA	30587	0.040	0.058	0.200	89885	0.047	0.062	0.147
RD	30587	0.104	0.008	0.325	89885	0.086	0.015	0.231
TANG	30587	0.306	0.221	0.260	89885	0.261	0.196	0.215
CASH	30587	0.189	0.103	0.211	89885	0.183	0.117	0.187
LEV	30587	0.238	0.210	0.230	89885	0.225	0.215	0.198
MTB	30587	2.450	1.824	2.107	89885	2.372	1.893	1.818
DIVDUM	30587	0.575	1.000	0.494	89885	0.575	1.000	0.494
PROFIT	30587	0.128	0.139	0.196	89885	0.139	0.143	0.129

Table 1 reports descriptive statistics for treatment and control sample. All variables are defined in Appendix A.

Table 2
Newspaper Closures and Analyst Forecast Frequency

Dependent Variable: Freq

	(1)		**(2)**	
	Coeff.	**t-Stat.**	**Coeff.**	**t-Stat.**
Newspaper Closure	**-0.051**	**-5.94*** **	**-0.051**	**-5.88*** **
Controls of analyst experiences				
Firm_Coverage	0.010	3.91***	0.010	3.88***
Log (Analyst Experience)	-0.022	-7.98***	-0.025	-8.55***
Log (Firm_Experience)	-0.004	-1.85*	-0.002	-1.12
Control of Brokerage resource				
Broker_Size	-0.005	-2.93***	-0.004	-2.51**
Control of analyst coverage				
Analyst_Coverage	0.149	58.07***	0.148	57.01***
Controls of firm characteristics				
SIZE	0.192	62.88***	0.190	61.54***
ROA	-0.093	-8.22***	-0.092	-8.16***
RD	0.132	12.50***	0.125	11.73***
TANG	0.408	22.12***	0.398	21.47***
CASH	0.043	3.69***	0.040	3.37***
LEV	0.012	1.42	0.012	1.41
MTB	-0.012	-17.58***	-0.012	-17.59***
DIVDUM	-0.053	-12.27***	-0.052	-12.11***
PROFIT	-0.131	-8.58***	-0.133	-8.67***
Firm Fixed Effects	**YES**		**NO**	
Firm×Analyst Fixed Effects	**NO**		**YES**	
State×Year Fixed Effects	**YES**		**YES**	
Year Fixed Effects	**YES**		**YES**	
S.E. clustering by Firm-Pair	**YES**		**YES**	
Adjusted R^2	**0.257**		**0.857**	
Model p-value	**<0.0001**		**<0.0001**	
N	120472		120472	

Table 2 reports the difference-in-differences regression results of the impact of staggered local newspaper closures on analysts' forecast frequency. In all regressions, coefficient estimates and p-values are based on robust standard errors clustered at the firm level. All variables are as defined in Appendix A.

***, ** and * denote significance at 1%, 5% and 10% levels (two tailed), respectively.

Table 3
Newspaper Closures and Analyst Forecast Timeliness

Dependent Variable: Timeliness

	(1)		(2)	
	Coeff.	**t-Stat.**	**Coeff.**	**t-Stat.**
Newspaper Closure	**-0.265**	**-2.97*** **	**-0.271**	**2.33** **
Controls of analyst experiences				
Firm_Coverage	0.043	1.72*	0.113	0.19
Log (Analyst Experience)	0.034	2.12**	0.365	0.75
Log (Firm_Experience)	0.054	3.25***	-0.359	-0.97
Control of Brokerage resource				
Broker_Size	0.053	4.37***	-0.525	-0.82
Control of analyst coverage				
Analyst_Coverage	-0.380	-9.85***	0.055	0.21
Controls of firm characteristics				
SIZE	-0.397	-12.31***	-0.226	-0.51
ROA	0.793	5.15***	1.388	0.88
RD	0.003	8.21***	-0.002	-0.48
TANG	-1.118	-4.77***	1.651	0.37
CASH	-0.615	-4.01***	1.912	0.71
LEV	-1.591	-13.78***	3.449	1.72
MTB	0.031	2.76***	0.145	0.89
DIVDUM	-0.452	-8.46***	1.300	1.41
PROFIT	-0.417	-1.87*	0.324	0.11
|REV|	0.001	1.03	-0.019	-0.03
Firm Fixed Effects	**YES**		**NO**	
Firm×Analyst Fixed Effects	**NO**		**YES**	
State×Year Fixed Effects	**YES**		**YES**	
Year Fixed Effects	**YES**		**YES**	
S.E. clustering by Firm-Pair	**YES**		**YES**	
Adjusted R^2	**0.466**		**0.795**	
Model p-value	**<0.0001**		**<0.0001**	
N	108430		108430	

Table 3 reports the difference-in-differences regression results of the impact of staggered local newspaper closures on analysts' forecast timeliness. In all regressions, coefficient estimates and p-values are based on robust standard errors clustered at the firm level. All variables are as defined in Appendix A.

***, ** and * denote significance at 1%, 5% and 10% levels (two tailed), respectively.

Table 4
Newspaper Closures and Analyst Forecast Accuracy

Dependent Variable: Accuracy

	(1)		(2)	
	Coeff.	**t-Stat.**	**Coeff.**	**t-Stat.**
Newspaper Closure	**-0.529**	**-3.81*** **	**-0.701**	**-4.53*** **
Controls of analyst experiences				
Firm_Coverage	0.011	0.35	0.158	2.27**
Log (Analyst Experience)	0.023	1.08	-0.161	-2.12**
Log (Firm_Experience)	-0.062	-2.91***	0.010	0.19
Control of Brokerage resource				
Broker_Size	0.017	1.09	-0.077	-1.76*
Control of analyst coverage				
Analyst_Coverage	-0.243	-3.34***	-0.258	-3.51***
Controls of firm characteristics				
SIZE	-0.085	-1.08	-0.057	-0.72
ROA	-1.942	-6.72***	-1.937	-6.68***
RD	0.013	0.05	0.051	0.19
TANG	-0.183	-0.39	-0.015	-0.03
CASH	-1.770	-5.89***	-1.760	-5.81***
LEV	-0.483	-2.25**	-0.512	-2.37**
MTB	0.031	1.82*	0.032	1.83*
DIVDUM	0.460	4.17***	0.429	3.87***
PROFIT	0.998	2.55**	0.986	2.50**
Firm Fixed Effects	**YES**		**NO**	
Firm×Analyst Fixed Effects	**NO**		**YES**	
State×Year Fixed Effects	**YES**		**YES**	
Year Fixed Effects	**YES**		**YES**	
S.E. clustering by Firm-Pair	**YES**		**YES**	
Adjusted R^2	**0.156**		**0.330**	
Model p-value	**<0.0001**		**<0.0001**	
N	120472		120472	

Table 4 reports the difference-in-differences regression results of the impact of staggered local newspaper closures on analysts' forecast accuracy. In all regressions, coefficient estimates and p-values are based on robust standard errors clustered at the firm level. All variables are as defined in Appendix A.

***, ** and * denote significance at 1%, 5% and 10% levels (two tailed), respectively.

Table 5
DiD Regression of Newspaper Closures and Informativeness of Analyst Forecast Revision
Dependent Variable: CAR_REV

	(1)		(2)	
	Coeff.	**t-Stat.**	**Coeff.**	**t-Stat.**
Newspaper Closure	**-0.004**	**-3.37*** **	**-0.005**	**-2.59*** **
Controls of analyst experiences				
Firm_Coverage	0.000	-0.88	0.000	-0.54
Log (Analyst Experience)	0.000	0.16	-0.001	-0.89
Log (Firm_Experience)	0.000	-0.67	-0.001	-1.12
Control of Brokerage resource				
Broker_Size	0.000	-1.97**	0.001	1.51
Control of analyst coverage				
Analyst_Coverage	-0.004	-6.74***	0.000	-0.41
Controls of firm characteristics				
SIZE	-0.001	-2.74***	-0.005	-5.37***
ROA	0.044	16.09***	0.030	7.57***
RD	0.000	-4.66***	0.000	-5.27***
TANG	-0.006	-1.92*	-0.012	-2.54**
CASH	0.004	2.19**	0.004	1.41
LEV	-0.002	-1.58	-0.007	-3.31***
MTB	0.004	23.13***	0.004	14.03***
DIVDUM	0.000	-0.61	0.001	1.11
PROFIT	-0.036	-9.70***	-0.035	-6.09***
|REV|	0.024	68.45***	0.028	60.12***
Firm Fixed Effects	**YES**		**NO**	
Firm×Analyst Fixed Effects	**NO**		**YES**	
State×Year Fixed Effects	**YES**		**YES**	
Year Fixed Effects	**YES**		**YES**	
S.E. clustering by Firm-Pair	**YES**		**YES**	
Adjusted R^2	**0.089**		**0.167**	
Model p-value	**<0.0001**		**<0.0001**	
N	170222		170222	

Table 5 reports the difference-in-differences regression results of the impact of staggered local newspaper closures on the price reaction to analysts' forecast revisions. In all regressions, coefficient estimates and p-values are based on robust standard errors clustered at the firm level. All variables are as defined in Appendix A.
***, ** and * denote significance at 1%, 5% and 10% levels (two tailed), respectively.

Table 6
Newspaper Closures and Informativeness of Analyst Stock Recommendation
Dependent Variable: CAR_RECOMM

	(1)		(2)	
	Coeff.	**t-Stat.**	**Coeff.**	**t-Stat.**
Newspaper Closure	**-0.006**	**-2.18*** **	**-0.014**	**-1.98** **
Controls of analyst experiences				
Firm_Coverage	0.000	-0.66	-0.004	-0.64
Log (Analyst Experience)	0.001	1.33	0.005	0.96
Log (Firm_Experience)	0.000	0.56	0.001	0.25
Control of Brokerage resource				
Broker_Size	-0.001	-4.09***	0.001	0.47
Control of analyst coverage				
Analyst_Coverage	-0.009	-8.40***	-0.008	-1.78*
Controls of firm characteristics				
SIZE	-0.002	-1.98**	0.003	0.79
ROA	0.004	1.14	0.009	0.72
RD	0.000	0.43	0.000	-0.83
TANG	-0.018	-2.48**	-0.124	-1.67*
CASH	-0.001	-0.22	-0.037	-1.15
LEV	-0.001	-0.42	-0.009	-0.34
MTB	0.004	14.94***	0.003	2.73***
DIVDUM	0.000	0.06	-0.026	-1.76*
PROFIT	0.024	4.61***	0.021	1.22
ΔRECOM	-0.020	-89.81***	-0.019	-55.92***
Firm Fixed Effects	**YES**		**NO**	
Firm×Analyst Fixed Effects	**NO**		**YES**	
State×Year Fixed Effects	**YES**		**YES**	
Year Fixed Effects	**YES**		**YES**	
S.E. clustering by Firm-Pair	**YES**		**YES**	
Adjusted R^2	**0.266**		**0.795**	
Model p-value	**<0.0001**		**<0.0001**	
N	58006		58006	

Table 6 reports the difference-in-differences regression results of the impact of staggered local newspaper closures on the price reaction to analysts' stock recommendation changes. In all regressions, coefficient estimates and p-values are based on robust standard errors clustered at the firm level. All variables are as defined in Appendix A.

***, ** and * denote significance at 1%, 5% and 10% levels (two tailed), respectively.

Table 7
Exploring Variation in News Content, Sentiment and Subcategories

Panel A: Conditional on Content and Tone of News

	News Content and Sentiment			
Proxy=	**First News**		**Negative News**	
	(1)		**(2)**	
	Coeff.	**t-Stat.**	**Coeff.**	**t-Stat.**
Newspaper Closure	-0.001	-0.57	-0.003	-1.44
Newspaper Closure*Proxy	**-0.009**	**-3.27*** **	**-0.007**	**-2.24** **
Proxy	0.010	3.84***	0.005	1.61
Firm Fixed Effects	YES		YES	
Firm×Analyst Fixed Effects	YES		YES	
State×Year Fixed Effects	YES		YES	
Year Fixed Effects	YES		YES	
S.E. clustering by Firm-Pair	YES		YES	
Adjusted R^2	**0.175**		**0.195**	
Model p-value	**<0.0001**		**<0.0001**	
N	170222		170222	

Panel B: Conditional on Types of News

	Subcategories of News			
Proxy=	**Earnings News**		**Legal News**	
	(1)		**(2)**	
	Coeff.	**t-Stat.**	**Coeff.**	**t-Stat.**
Newspaper Closure	-0.002	-0.82	0.000	0.04
Newspaper Closure*Proxy	**-0.012**	**-3.83*** **	**-0.009**	**-2.79*** **
Proxy	0.007	2.63***	-0.002	-0.41
Firm Fixed Effects	YES		YES	
Firm×Analyst Fixed Effects	YES		YES	
State×Year Fixed Effects	YES		YES	
Year Fixed Effects	YES		YES	
S.E. clustering by Firm-Pair	YES		YES	
Adjusted R^2	**0.206**		**0.167**	
Model p-value	**<0.0001**		**<0.0001**	
N	170222		170222	

Table 7 reports the cross-sectional results conditional on news content, tone, and type. Dependent variable is the informativeness of analyst research, measured by price reaction to analyst forecast revision. Panel A reports the results conditional on the information content and tone of the news about a firm before the coverage shocks, measured by initial news coverage and negative tone of the news. Panel B reports the results conditional on subcategories of the news about a firm before the coverage shocks, measured by earnings news and legal news. In all regressions, coefficient estimates and p-values are based on robust standard errors clustered at the firm level. All variables are as defined in Appendix A.

***, ** and * denote significance at 1%, 5% and 10% levels (two tailed), respectively.

Table 8
Exploring Variation in Analysts' Uncertainty, Capability and Resource Constraint

Panel A: Conditional on Analysts' Information Uncertainty

	Analyst Information Uncertainty			
Proxy=	**Complex Firm**		**Opaque Firm**	
	(1)		**(2)**	
	Coeff.	**t-Stat.**	**Coeff.**	**t-Stat.**
Newspaper Closure	0.001	1.35	-0.001	-0.55
Newspaper Closure*Proxy	**-0.016**	**-5.02*** **	**-0.005**	**-2.18** **
Proxy	0.003	0.96	-0.002	-1.93
Firm Fixed Effects	**YES**		**YES**	
Firm×Analyst Fixed Effects	**YES**		**YES**	
State×Year Fixed Effects	**YES**		**YES**	
Year Fixed Effects	**YES**		**YES**	
S.E. clustering by Firm-Pair	**YES**		**YES**	
Adjusted R^2	**0.206**		**0.207**	
Model p-value	**<0.0001**		**<0.0001**	
N	170222		170222	

Panel B: Conditional on Analysts' Capability and Resource Constraint

	Analyst Capability and Resource Constraint			
Proxy=	**Less Experienced**		**Small Broker**	
	(1)		**(2)**	
	Coeff.	**t-Stat.**	**Coeff.**	**t-Stat.**
Newspaper Closure	-0.005	-2.54**	0.000	0.14
Newspaper Closure*Proxy	**-0.003**	**-1.82***	**-0.002**	**-2.22** **
Proxy	0.001	1.20	-0.004	-1.60
Firm Fixed Effects	**YES**		**YES**	
Firm×Analyst Fixed Effects	**YES**		**YES**	
State×Year Fixed Effects	**YES**		**YES**	
Year Fixed Effects	**YES**		**YES**	
S.E. clustering by Firm-Pair	**YES**		**YES**	
Adjusted R^2	**0.167**		**0.206**	
Model p-value	**<0.0001**		**<0.0001**	
N	170222		170222	

Table 8 reports the cross-sectional results conditional on analyst uncertainty, capability, and resource constraint. Dependent variable is the informativeness of analyst research, measured by price reaction to analyst forecast revision. Panel A reports the results conditional on analysts' information uncertainty about the covered firm, measured by firm complexity and opacity. Panel B reports the results conditional on analysts' experiences and resource constraints, measured by the number of years covering the firm and the size of affiliated brokerage houses. In all regressions, coefficient estimates and p-values are based on robust standard errors clustered at the firm level. All variables are as defined in Appendix A.

***, ** and * denote significance at 1%, 5% and 10% levels (two tailed), respectively.

Table 9
OLS Regression of Media News and Analyst Forecast Accuracy

Dependent Variable: Accuracy

	Pooled (1)		**Upward Bias (2)**		**Downward Bias (3)**	
	Coeff.	**t-Stat.**	**Coeff.**	**t-Stat.**	**Coeff.**	**t-Stat.**
NewsCount	**0.261**	**3.45*** **	**0.042**	**0.42**	**0.317**	**2.33** **
|NewsTone|	0.035	2.20**	0.063	3.00***	-0.021	-0.72
Controls of analyst experiences						
Firm_Coverage	0.157	1.63	0.155	1.16	0.061	0.37
Log (Analyst Experience)	-0.235	-2.46**	-0.256	-1.91	-0.245	-1.51
Log (Firm_Experience)	0.069	0.96	-0.020	-0.20	0.086	0.73
Control of Brokerage resource						
Broker_Size	-0.145	-2.32**	-0.028	-0.32	-0.160	-1.51
Control of analyst coverage						
Analyst_Coverage	-0.068	-0.72	0.505	3.98***	-0.747	-4.50***
Controls of firm characteristics						
SIZE	-0.014	-0.11	-0.243	-1.31	0.047	0.20
ROA	-2.697	-5.50***	-2.332	-4.08***	4.018	3.32***
RD	0.058	0.70	-0.021	-0.19	0.621	3.60***
TANG	2.854	4.12***	4.539	4.67***	-3.000	-2.49**
CASH	-0.429	-1.15	-1.673	-3.06***	1.149	1.84*
LEV	-0.079	-0.30	0.235	0.70	-0.163	-0.31
MTB	0.140	3.72***	-0.145	-2.58***	0.388	6.17***
DIVDUM	-0.184	-1.21	0.304	1.34	-1.001	-4.16***
PROFIT	1.343	1.86*	-2.814	-2.97***	3.755	2.55**
Firm×Analyst Fixed Effects	**YES**		**YES**		**YES**	
Year Fixed Effects	**YES**		**YES**		**YES**	
S.E. clustering by Firm	**YES**		**YES**		**YES**	
Adjusted R^2	**0.343**		**0.443**		**0.472**	
Model p-value	**<0.0001**		**<0.0001**		**<0.0001**	
N	61621		32934		28687	

Table 9 reports the additional OLS analysis of news coverage, news tone, and analysts' forecast accuracy. In all regressions, coefficient estimates and p-values are based on robust standard errors clustered at the firm level. All variables are as defined in Appendix A.

***, ** and * denote significance at 1%, 5% and 10% levels (two tailed), respectively.

Table 10
OLS Regression of Media News and Analyst Research Informativeness

Dependent Variable: CAR

	Pooled (1)		**Upgrade (2)**		**Downgrade (3)**	
	Coeff.	**t-Stat.**	**Coeff.**	**t-Stat.**	**Coeff.**	**t-Stat.**
NewsCount	**0.003**	**6.51*** **	**0.001**	**0.83**	**-0.004**	**-5.83*** **
|NewsTone|	0.000	3.15***	0.000	0.95	-0.001	-3.72***
Controls of analyst experiences						
Firm_Coverage	0.000	0.16	-0.001	-1.06	-0.001	-0.84
Log (Analyst Experience)	0.000	-0.68	-0.001	-1.11	0.000	-0.03
Log (Firm_Experience)	0.000	0.23	0.000	-0.20	0.000	-0.22
Control of Brokerage resource						
Broker_Size	0.001	3.32***	0.002	3.43***	-0.001	-1.83*
Control of analyst coverage						
Analyst_Coverage	0.000	-0.48	-0.006	-6.20***	-0.004	-3.91***
Controls of firm characteristics						
SIZE	-0.001	-0.61	-0.002	-2.04**	-0.003	-2.34**
ROA	-0.001	-0.22	0.015	2.80***	0.007	1.57
RD	-0.002	-2.92	-0.005	-5.73***	-0.002	-1.52
TANG	-0.003	-0.62	0.000	-0.06	0.005	0.83
CASH	-0.013	-4.67	-0.007	-1.93*	0.016	3.88***
LEV	0.004	2.00	-0.003	-1.33	-0.012	-4.44***
MTB	0.000	0.71	0.004	11.43***	0.003	7.61***
DIVDUM	0.001	1.06	0.006	4.93***	0.004	2.92***
PROFIT	0.002	0.47	-0.040	-5.63***	-0.029	-4.00***
|REV|	0.013	28.38***	0.008	13.65***	-0.019	-25.46***
Firm×Analyst Fixed Effects	**YES**		**YES**		**YES**	
Year Fixed Effects	**YES**		**YES**		**YES**	
S.E. clustering by Firm	**YES**		**YES**		**YES**	
Adjusted R^2	**0.179**		**0.262**		**0.268**	
Model p-value	**<0.0001**		**<0.0001**		**<0.0001**	
N	194052		194052		194052	

Table 10 reports the additional OLS analysis of news coverage, news tone, and price reaction to analysts' forecast revisions. In all regressions, coefficient estimates, and p-values are based on robust standard errors clustered at the firm level. All variables are as defined in Appendix A.

***, ** and * denote significance at 1%, 5% and 10% levels (two tailed), respectively.