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Friends in media: Implications of media connections for analyst forecast optimism

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ABSTRACT

We investigate the effect of corporate executives' connections with financial media on analyst forecast optimism. Some studies document that managers use their connections to benefit the firm. Alternatively, other studies show that managers use their connections to benefit themselves at the expense of the firm. Thus, it is difficult to predict ex-ante whether executives use their media connections to enhance information efficiency or distort information environment. We propose two hypotheses on the impact of financial media connections: information efficiency and manipulation. We estimate managerial media connection by using the BoardEx database, and apply standard OLS regression, mediation analysis, propensity score matching, 2-SLS instrumental variable regressions, and difference-in-difference regressions to test the two alternate hypothesis. Consistent with the manipulation hypothesis, our results suggest that corporate executives use media connections to exacerbate analyst forecast optimism. Mediation analysis suggests that media connections are related to not only more news coverage but also more positive news sentiment. We further find that managerial incentives and board monitoring moderates the relationship between media connections and analyst forecast optimism. Our study makes several contributions to academic literature and is interesting to regulators and investors. As corporate executives tend to exploit their friendship with the media to achieve enhanced analyst forecast optimism, it would have a negative impact on the efficiency of the capital markets. Our results suggest that regulators and investors should more closely scrutinize the social ties of corporate executives.

1. Introduction

> "Chatting with reporters makes them smarter and they return the favor by raising your profile. First, you are source, then a friend, and then they'll start calling you visionary. With the best reporters, [Warren] Buffet is always available as a source."
>
> Cunningham (2017), *Medium*

> "Some companies have more influence over your media organization than others. If they make the right complaint, next thing you know you can see a journalist get moved to a different beat."
>
> Anonymous journalist interviewed in Call, Emett, Maksymov, and Sharp (2022)

Warren Buffet, the billionaire financier, befriends journalists and uses media connections to convey his message to the broader investing public. The anecdote from *Medium* implies that company executives can serve as a source for journalists and convey their message to investors. Alternatively, executives may use their connections to influence coverage of the firm. Financial journalists interviewed in a recent study by Call et al. (2022) state that they face retaliation for unfavorable articles about a firm. The journalists also state that sometimes company management complains to editors, which might end up in demotion, as quoted by an anonymous journalist above. This anecdotal example suggests that managers may use their media connections to generate more positive news coverage and suppress negative news about the firm, which is not informative for investors and capital markets.

These anecdotal examples suggest that corporate insiders can use their media connections to inform and mislead capital markets. Although prior studies investigate the role of media in financial markets (Bushee, Core, Guay, & Hamm, 2010; Fang & Peress, 2009; Gentzkow &

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Shapiro, 2006; Reuter & Zitzewitz, 2006), there is limited research on the effect of corporate executives' media connections. Our study attempts to fill the void in this area by investigating the implications of media connections on a firm's information environment. Miller and Skinner (2015, 233) call for "a fuller understanding of the media". The authors also mention that this "would contribute significantly to our overall understanding of information flow in financial markets". Our research responds to this call. Specifically, we determine that media connection is an important channel through which information flows from company to news outlets. Call et al. (2022, 7) mention that their study motivates "future research that examines how a broader set of CEO personality traits influence the nature and flow of information in financial markets". Although our study does not exclusively focus on CEO's traits or connections, we determine that executives' connections influence the nature (i.e., tone) and flow of information (i.e., number of news articles) in financial markets. We focus on the media connections of executive directors and label them as managers or corporate insiders throughout the paper.

The realization that managers' connections can serve as a double-edged sword has led to research on the social networks of executives. Several studies document that managers use their connections to benefit the firm.[1] On the contrary, other studies demonstrate that managers use their connections to benefit themselves at the expense of the firm.[2] Thus, it is difficult to predict ex-ante whether executives use their media connections to enhance information efficiency or distort information environment, as shown in the examples above. It is also possible that while some managers use their media connections to improve information efficiency, others might use the media connections to increase analyst forecast optimism. Therefore, we propose two hypotheses: information efficiency and manipulation. We would like to note that these hypotheses are not mutually exclusive.

Managers may use their media connections to provide nonmaterial non-public information to capital markets. Further, having media connections allows managers to gain access to media outlets, which provides an opportunity to broadly discuss the company's prospects. Journalists are also likely to access more information through social ties with managers due to the difficulty of sourcing news articles (Call et al., 2022). Media connections also enable managers to reach a larger potential investor audience. Thus, managers may use their media connections to inform investors on a timely basis or disseminate information to a broader audience, which enhances the information environment. We call this the information efficiency hypothesis.

Alternatively, managers may use their media connections to pursue their own agenda. Media has the power to frame the description of an event in either a positive or negative way (Guest, 2021; Solomon, 2012). Journalists are more likely to cite analysts with sell recommendation over analysts with buy recommendation (Call et al., 2022), suggesting that sell recommendation attracts more media attention. Therefore, executives have incentives to use their media connections to create analyst forecast optimism, which would prevent or reduce the likelihood of receiving a sell recommendation by an analyst. Thus, using media connections, managers can spin a story to their advantage, including the one that involves negative news events. Managers also may use media connections to prevent the spread of negative information. We call this the *manipulation* hypothesis. Information efficiency and manipulation hypotheses are not mutually exclusive as some managers may use their connections to enhance information environment, whereas other managers might use their media connections to create a more optimistic picture of the firm that does not reflect the underlying economic reality. In our study, we analyze the aggregate and net effect of the media connections at firm-year level.

We use the BoardEx database to determine managerial connections with financial media. We identify all the directors who have worked in these 'Financial Media Firms' and categorize them as 'Financial Media Directors'. We use BoardEx to plot the connections of all the non-media firms in the BoardEx universe with the 'Financial Media Directors' identified in the previous step and denote each node as one media connection. The connections with media directors may have been established through prior employment, education, and/or social activities. Once the connections are identified at the director level, we aggregate the media connections by firm-year.

Our results lend support to the manipulation hypothesis, as we find that media connection is positively associated with analyst forecast optimism. Results suggest that managers use their media connections to create a more optimistic picture of the firm that may not reflect the underlying economic reality, which increases analysts' forecast optimism. Our results are statistically and economically significant. Analyst forecast optimism increases by 20.10% of the sample mean when there is a shift from the 25th to the 75th percentile of the distribution of financial media connection.

Next, we investigate how financial media connections increase analyst forecast optimism (i.e., the channels of media connections). Results from the mediation analysis show that financial media connection is associated with not only more news coverage but also more positive news sentiment. Our results suggest that more news coverage is not necessarily beneficial for shareholders, particularly if the coverage is through the connections of the corporate managers. In untabulated analysis, we examine the association between media connections and news sentiment immediately before earnings announcements. Consistent with the manipulation hypothesis, we find that the firms with a larger number of financial media connections are more (less) likely to receive positive (negative) news coverage before earnings announcements. These results demonstrate that corporate managers use their media connections to receive favorable news coverage, which is not necessarily informative for shareholders.

We further examine the effect of financial media connections on the analyst forecast optimism through cross-sectional analysis. Since we find preliminary support for the *manipulation* hypothesis, we conjecture that managers may use media manipulation as a substitute for financial reporting manipulation (i.e., earnings management). As oversight over financial reporting by the board increases, alternative types of manipulation (i.e., spinning of information through media outlets) may become more attractive. Results of the cross-sectional analysis suggest that in the presence of more independent boards, where monitoring is higher, corporate managers are more likely to use media connections to increase analyst forecast optimism. Furthermore, the effect of media connection on analysts' forecast optimism is stronger in the lower-earnings management firms. This analysis suggests that the firms with greater financial media connections are more likely to use media connections to increase analyst forecast optimism in lieu of earnings management.

We employ propensity score matching (PSM), entropy balancing approach, and instrumental variable (IV) estimation to mitigate endogeneity concerns. Further, we estimate a quasi-natural experiment by exploiting the turnover of financial media-connected executives. Results from the difference-in-difference regression suggest that analyst forecast optimism reduces following the departure of financial media-connected executives. In other words, a reduction in media connections caused by the turnover of media-connected executives leads to a better information environment. This analysis lends further support to the

[1] For example, managers use their connections to lower cost of capital (Engelberg et al., 2012; Javakhadze et al., 2016), improve credit ratings (Khatami et al., 2016; Skousen et al., 2018), encourage greater innovation (Faleye et al., 2014; Helmers, Patnam, & Rau, 2017), and enhance firm performance (Cai & Sevilir, 2012; Kim, 2005; Larcker, So, & Wang, 2013).

[2] For example, a higher number of managerial social ties is associated with lower quality of financial reporting (Bruynseels & Cardinaels, 2014), greater likelihood of fraud contagion (Fich & Shivdasani, 2007), lower firm performance (Fracassi & Tate, 2012), and poorer corporate governance (Falato, Kadyrzhanova, & Lel, 2014).

manipulation hypothesis.

We would like to caution readers that not all media connections necessarily help firms manipulate the information environment. For example, Elizabeth Holmes was accused by *The Wall Street Journal* (*WSJ*, hereafter) writer of running a fraud blood-testing company, Theranos. Ms. Holmes attempted to prevent the publication of the news by reaching out to Rupert Murdoch, who was chairman and CEO of News Corporation, the owner of the *WSJ* (Khorram, 2021). Mr. Murdoch refused to intervene on behalf of Elizabeth Holmes and the *WSJ* published the story about questionable business practices in Theranos, which eventually led to the demise of the company. This anecdotal example demonstrates that managers cannot always use media connections to manipulate information.

Our study makes several contributions to academic literature and is interesting to regulators and investors because it has public policy implications. We add to the nascent literature on media connections. Miller and Skinner (2015, 232-233) encourage researchers to examine "the media's interaction with other players in financial markets". The authors mention that this area is still underdeveloped and a fuller understanding "would contribute significantly to our overall understanding of information flow in financial markets". Call et al. (2022, 3) state that "we need to better understand the nature of these interactions and the potential influence different market participants may exert on financial journalism, and vice versa". Our research responds to these calls. Findings in our research suggest that executives use their media connections to exert influence on media that generates more news coverage, and the tone of the coverage is more positive. Hossain and Javakhadze (2020) investigate mergers and acquisitions and find that acquirers' media connection is associated with higher bid announcement return, greater likelihood of deal completion, and lower post-merger performance. Gurun (2020) focuses on board members with media experience, which the author defines as media professionals (MP). The author determines that firms that have board members with media experience receive greater coverage. Examining Chinese markets, Ru, Xue, Zhang, and Zhou (2020) determine that connections between media executives and firms positively affect media coverage. Yan, Wang, Wang, and Chan (2023) examine the effect of media connections on IPO and find that media connection helps achieve more frequent and more positive media coverage, which facilitates reduced IPO underpricing. Di Giuli and Laux (2022) report that media connection of directors act as a substitute for external governance.

Our study also contributes to the growing literature on corporate executives' social networks. While some studies demonstrate that company insiders' connections benefit the firm (Javakhadze, Ferris, & French, 2016; etc.), others suggest that company insiders opportunistically use their connections to benefit themselves at the expense of the firm (Bruynseels & Cardinaels, 2014). Our study expands this literature by investigating corporate executives' connections with an important yet under-examined intermediary in the financial markets – the media.

Next, we study the impact of media on capital markets. Findings of Bushee et al. (2010) and Miller (2006) suggest that media increases monitoring of firms, either by providing new information or disseminating existing information to a broader investing public. Blankespoor and Zhu (2018) find that "robo-journalism" increases firms' trading volume and liquidity, which has implications for market efficiency. Other studies such as Dyck and Zingales (2003) and Gurun and Butler (2012) conclude that media biases information, thus, media monitoring is not necessarily beneficial to capital markets. Similarly, we find that media connections could be exploited to increase analyst forecast optimism, which is consistent with the findings of prior studies that document media bias.

Finally, our study has public policy implications. This study is of interest to regulators and investors because we determine that friends in media can facilitate enhanced analyst forecast optimism, which has a negative impact on the efficiency of capital markets. Our results suggest that regulators and investors should more closely scrutinize the media connections of executives. Regulators also should carefully review the acquisition of media outlets by non-media firms, as it might be an attempt by the non-media executives to buy favor with the media connections. The results also suggest that investors should cautiously interpret the content of the information provided through certain media outlets, especially if the executives of media outlets and covered firms have connections.

The rest of our paper is organized as follows. We summarize the prior literature and develop hypotheses in Section 2. We continue with a detailed description of the media connections measure in Section 3 and introduce the research design. Results and additional analyses are discussed in Section 4. Section 5 reports the robustness tests and Section 6 addresses endogeneity concerns. Finally, we conclude the paper in Section 7.

2. Literature review and hypothesis development

2.1. Factors affecting analyst forecast optimism

Financial analysts are significant players in capital markets, therefore, their forecast optimism has implications for the efficiency of markets. Analyst forecast optimism arises when financial analysts make earnings forecast that are higher than the actual earnings numbers reported by the firm (Engelberg, McLean, & Pontiff, 2020). Optimism in analysts' forecast is costly for investors, and reducing optimism could result in higher return for investors who rely on analysts' recommendations (Kadous, Krische, & Sedor, 2006). Several factors impact analyst forecast optimism and a firm's information environment is one of the key factors (Kadous et al., 2006). Analysts rely on publicly available information as well as private communication with management when making earnings forecast (Brown, Call, Clement, & Sharp, 2015). Since private communication data are not available, research primarily focuses on publicly available information that shapes a firm's information environment, which has implications for analyst forecast optimism. For example, larger firms have better information environment, which improves analyst forecast optimism. Analysts forecast optimism also goes down as the earnings date approaches because more information becomes public, which makes analysts to adjust their forecasts (Kadous et al., 2006). Thus, forecast horizon is another factor that determines analyst forecast optimism. We elaborate on these factors in the research design section, where we discuss the control variables impacting forecast optimism.

2.2. Social network and its conduits

Woolcock (1998) states that social capital is the aggregation of information, trust, and reciprocity among members of the same social network. Managers can use social networks in various ways, including to gather and disseminate information (Cohen, Frazzini, & Malloy, 2010), create trust and enforce contracts (Javakhadze et al., 2016), access lower cost of capital (Engelberg, Gao, & Parsons, 2012), engage in risky behavior (Faleye, Kovacs, & Venkateswaran, 2014), and appoint friends into positions of power for opportunistic purposes (Bruynseels & Cardinaels, 2014; Khanna, Kim, & Lu, 2015), among others.

Information flow is an inherent part of social connections as connections facilitate transfer of information. Cohen et al. (2010) determine that school ties between analysts and executives increase performance of analyst recommendations. Gu, Li, Yang, and Li (2019) show that having connections with mutual fund managers facilitates information acquisition about the firms in the mutual funds' holdings. Cai, Dhaliwal, Kim, and Pan (2014) determine that board connections through shared directors affects firms' disclosure policies. Jung (2013) finds similar results using investor connections (i.e., investor overlap). In a recent survey study, Call et al. (2022) determine that executive connections are important for financial journalists when developing news articles. These studies demonstrate the information flow channel of social capital,

which is the focus of our study.

Social capital, by creating trust and reciprocity among members of the same social network, discourages opportunistic behavior and serves as a contract enforcement mechanism (Bhandari, Mammadov, Shelton, & Thevenot, 2018; Javakhadze et al., 2016). Fear of potential loss of social capital constrains opportunistic behavior and creates implicit pressure on managers to act in an honest manner (Bhandari, Mammadov, Shelton, & Thevenot, 2018; Javakhadze et al., 2016). Consistent with this argument, Bhandari, Mammadov, Shelton, and Thevenot (2018) conclude that well-connected managers are less likely to engage in earnings management.

2.3. Significance of media coverage in financial markets

Our study focuses on corporate insiders' connections with representatives of the financial media. Extant literature demonstrates the importance of active media management in financial markets. By analyzing the role of media in capital markets, several studies find that tone of media reporting predicts stock returns and trading activity of investors (e.g., Garcia, 2013; Liu & Han, 2020; Tetlock, 2007; Tetlock, Saar-Tsechansky, & Macskassy, 2008). Lee, Hutton, and Shu (2015) conclude that active media management reduces investors' reaction to negative news events. Similarly, Elliott, Hodge, and Sedor (2011) find that video disclosure attenuates the negative reaction of investors to restatement announcements compared to the press release announcements.

Kaniel and Parham (2017) find that even appearance in media may have significant business implications for firms, which demonstrates the importance of media coverage, particularly if the coverage is positive. Dang, Dang, Hoang, Nguyen, and Phan (2020) show that media coverage affects stock price synchronicity. Aman and Moriyasu (2022) find that media coverage improves stock liquidity. Further, Kaniel and Parham (2017) determine that mutual funds appearing in top 10 list of "Category Kings" of the *WSJ* experience 31% increase in capital flows during the post-publication quarter. The authors attribute this effect to the visibility of news as opposed to informational content, suggesting that placement of news is more important than content of news. In further analysis, Kaniel and Parham (2017) determine that mutual funds capitalize on this prominence by using it to promote the fund in other media outlets. Findings of this study demonstrate the importance of media coverage.

2.4. How do Media connections affect analyst forecast optimism?

Mosaic theory suggests that analysts gather public, non-public, and non-material information about a company to produce their investment thesis. A crucial yet overlooked source of non-material information is media coverage. Journalists reveal qualitative information (e.g., CEO's health, corporate culture) about companies that are unavailable in company disclosures or other information sources. This qualitative information adds value to constructing a complete picture for the analysts.

Financial analysts respond to news coverage by updating their research (Bradshaw, Lock, Wang, & Zhou, 2021; Frijns & Huynh, 2018). Bradshaw et al. (2021) determine that quantity of news coverage is positively associated with analysts' recommendation revisions, primarily explained by qualitative rather than quantitative information in the news.[3] The authors also find that tone of news coverage determines the direction of analysts' stock recommendation revision: negative (positive) news sentiment is associated with a downward (upward) revision. Results suggest that analysts make changes in their recommendations after processing news and the magnitude of change is greater for soft news. These studies suggest that media outlets influence analysts' decisions. Analysts have a significant influence on financial markets (Crane & Crotty, 2020). When analysts, particularly influential analysts, upgrade or downgrade a company's stock, the stock price reacts strongly to the change in analysts' recommendations. Therefore, managers may want to use their media connections to achieve positive news sentiment, which would increase analysts' forecast optimism (i.e., bias).

Another reason managers have incentives to manipulate press is that the business press has larger and broader audience compared to analyst reports and corporate filings (Bushee et al., 2010; Fang & Peress, 2009). Thus, managers may use their media connections to convey positive information about the firm to a broader audience, which include analysts as well as other market players such as institutional or retail investors.

Next, we discuss how senior executives may use their media connections to either enhance a firm's information environment (i.e., information efficiency hypothesis) or distort a firm's information environment (i.e., manipulation hypothesis). Based on that, we derive the testable hypotheses that predict the effect of media connections on analyst forecast optimism.

2.5. Information efficiency hypothesis

Several studies find that media enhances information efficiency in capital markets. Bushee et al. (2010) find that press coverage reduces information asymmetry and attenuates the information advantage of informed investors. Miller (2006) finds evidence that media monitors for accounting fraud either by spreading information from other sources (e.g., analysts, auditors) or through investigative journalism. Dai, Parwada, and Zhang (2015) reach a similar conclusion by demonstrating that media deters insider trading activity, which reduces profitability of insider trading. Kim, Jo, Ahn, and Yi (2022) find that media coverage increases investors' awareness about corporate misconduct. Lauterbach and Pajuste (2017) examines share class unifications and conclude that media promotes enhanced corporate governance. Rogers, Skinner, and Zechman (2016) document that media plays an important role in disseminating insider-trading news to the investment community, which affects security prices. Media outlets perform a monitoring duty through several channels: disseminating information (Amaya, Filbien, & Kooli, 2022; Bushee et al., 2010; Dai et al., 2015; Dyck & Zingales, 2003), facilitating investor attention (Huberman & Regev, 2001), and disciplining corporate misbehavior (Dyck, Morse, & Zingales, 2010; Dyck, Volchkova, & Zingales, 2008). Media outlets also induce socially responsible behavior (Brown & Deegan, 1998; Islam & Deegan, 2010).

These studies demonstrate the positive effect of media monitoring in capital markets and suggest that having connections to media outlets can benefit the firm in terms of a better information environment, which is consistent with social network literature showing that managers' connections add value to the firm. For example, managers use their connections to avail less expensive financing (Engelberg et al., 2012; Javakhadze et al., 2016), higher credit rating (Khatami, Marchica, & Mura, 2016; Skousen, Song, & Sun, 2018), and greater innovation (Faleye et al., 2014). As such, media connections potentially serve as an information channel for corporate insiders and may provide access to television shows and financial news channels (e.g., Bloomberg TV, CNBC). Information flow is faster through networks compared to formal channels (Cohen et al., 2010; Gu et al., 2019).

Contract enforcement mechanism of social capital suggests that journalists would conduct greater due diligence of the information shared by their corporate friends than by others with whom journalists do not share a social tie. In Call et al. (2022) survey study, financial journalists admit that having access to company management is important as information source. Thus, the contract enforcement mechanism would enhance information quality disseminated to public by journalists, thereby enhancing a firm's information environment and reducing analyst forecast optimism.

[3] Bradshaw et al. (2021) determine that soft news (i.e., qualitative information) is more costly to process compared to hard news (i.e., quantitative information).

Consistent with the above mentioned arguments, we predict that managers may use their media connections to improve information environment. Managers who have access to media connections can convey nonmaterial non-public information to capital markets or disseminate information to a broader audience, which can enhance the overall information environment. As a result, analyst forecast optimism would be lower for the media connected firms. We call this the information efficiency hypothesis based on which we make the following prediction:

H1a. *: Firms with a larger number of financial media connections have lower analyst forecast optimism (information efficiency hypothesis).*

2.6. Manipulation hypothesis

Guest (2021) mentions that journalists of the *WSJ* have a large latitude in interpreting information in firms' earnings releases, which has an impact on market's reaction to the firms' earnings news. Fedyk (2018) determines that positioning of news on front page of Bloomberg Terminal induces 280% higher trading volume and 180% larger price changes immediately after publication of the news. These studies suggest that journalists and media outlets have large latitude in presenting and interpreting information, which impacts stock prices. These studies also demonstrate the importance of media connections, where managers may use the media connections to interpret information more optimistically. It is not possible to change quantitative information (e.g., earnings or revenue numbers), but managers may use the media connections to put a positive spin on an information.

Solomon (2012) finds that companies use investor relations firms to spin positive news, which temporarily increases stock prices. Solomon defines media spin as increasing media coverage of the positive news relative to the negative news. This study demonstrates the importance of actively working with media. The author also determines that it is easier to spin non-earnings announcement news compared to earnings announcement news because non-earnings announcement news contain more soft information (i.e., qualitative information). Conducting further analysis, the author determines that investor relation firms' connections with reporters facilitate spinning out positive news for clients. Solomon (2012) uses geography to proxy for the connection between the client company and investment relations firm. In our study, we use a more direct approach and identify connections based on prior employment and/or educational history. We extend this study by focusing on firms' own connections with the media.

In a recent survey study, Call et al. (2022) determine that media connections are important for financial journalists when developing news articles. In the same survey study, journalists admit that they face negative personal consequences if they portray a company in an unfavorable light. One of the negative consequences is losing access to company management, which is important in providing exclusive information to journalists. Tips from management are important for journalists looking to break news (Call et al., 2022). Journalists also face more scrutiny from editors if the news articles are unfavorable (Call et al., 2022). One of the journalists interviewed by Call et al. (2022) states: "Some companies have more influence over your media organization than others. If they make the right complaint, next thing you know you can see a journalist get moved to a different beat." We conjecture that it is the media connections that allow some companies to have more influence over a media organization, particularly if the connections are with the media executives. Management can use these connections to retaliate against journalists who portray the company in an unfavorable light.

Business interests also create media bias. Advertising is the most significant source of revenue for media firms, which is why advertising dollars create potential media bias. Consistent with this argument, Reuter and Zitzewitz (2006) find that past advertisements of mutual funds are associated with the recommendation of those funds by the same media outlet. Similarly, Dewenter and Heimeshoff (2014) determine that a car manufacturer's advertising expenses are positively associated with the review score of the manufacturer's products. Gurun and Butler (2012) find similar results stating that local media reports are positively biased for local firms due the advertising revenue. Dyck and Zingales (2003) find evidence of a quid pro quo relationship between companies and journalists, which suggests that companies provide private information to journalists in exchange for a positive spin on the company news. Other studies determine that media misleads investors about a firm's potential (Ahern & Sosyura, 2014; Frankel & Li, 2004; Pollock & Rindova, 2003). In summary, prior research documents that media outlets cater to corporate interests. These studies show that media bias exists, suggesting that there is an ample opportunity for company insiders to use media connections to increase analyst forecast optimism.

Several studies demonstrate that managers use connections to benefit themselves, sometimes at the expense of shareholders. For example, Bruynseels and Cardinaels (2014), Khanna et al. (2015) and Fracassi and Tate (2012) find that CEO connections reduce oversight quality of corporate governance.

Furthermore, sell recommendation by analysts attracts negative media attention (Call et al., 2022), which is why managers have incentives to increase analyst forecast optimism and avoid receiving a sell recommendation.

In line with these arguments, we predict that corporate insiders opportunistically use media connections to increase analyst forecast optimism because media is prone to bias and serving managers' interests. We term this the manipulation hypothesis. Managers may use their media connections to spin a story and interpret information in a certain way. Using the manipulation hypothesis, we conjecture that corporate insiders use their financial media connections to increase analyst forecast optimism. Formally stated:

H1b. *: Firms with a larger number of financial media connections have higher analyst forecast optimism (manipulation hypothesis).*

Information efficiency and manipulation hypotheses are not mutually exclusive. While some firms or managers might use their media connections to enhance information environment, others might use the connections to increase analyst forecast optimism.

3. Research design

3.1. Sample selection

Table 1 presents the sample selection process (Panel A) and sample distribution by year (Panel B) and industry (Panel C). We use the BoardEx database to construct media connections sample, which starts in 1999. BoardEx started collecting data primarily for the directors/executives who have been in position since 1999. The database includes detailed information about the job history, educational background, and social background of executives (e.g., golf club membership, art museum board membership). Thus, the data allow us to identify the members of executive directors' networks. Information provided in the database also allows us to identify the position of executive directors' connections (e.g., whether the connected individual is a CEO, board member, banker, or journalist). We keep only the firm-year observations for which we can calculate at least one media connection. Thus, we do not assume zero media connections for firm-year observations for which we cannot find a media connection. Similar to prior studies, we exclude financial and utility industry firms because these firms are heavily regulated. We start with 9149 firm-year observations in the BoardEx-I/B/E/S matched dataset. Then, we merge the dataset with Compustat and CRSP databases. Our final sample size is 5526 firm-year observations, as seen in Panel A of Table 1.

Table 1
Sample selection and distribution by year and industry.

Panel A: Sample Selection	Obs.
Number of firm-year observations with at least one media connection in BoardEx - IBES matched dataset	9149
Less: Missing Compustat data match	40
Less: Missing CRSP data match	3165
Less: Firms with missing control variables	690
Final Data	5254

Panel B: Sample Distribution by Year		
Year	Obs.	Percent
2000	70	1.3%
2001	98	1.9%
2002	123	2.3%
2003	166	3.2%
2004	228	4.3%
2005	341	6.5%
2006	379	7.2%
2007	483	9.2%
2008	457	8.7%
2009	501	9.5%
2010	512	9.7%
2011	538	10.2%
2012	598	11.4%
2013	572	10.9%
2014	188	3.6%
Total	5254	100%

Panel C: Sample distribution by Industry			
FF Industry	Industry Name	Obs.	Percent
1	Consumer Non-Durables	280	5.3%
2	Consumer Durables	42	0.8%
3	Manufacturing	596	11.3%
4	Oil, Gas, and Coal Extraction and Products	96	1.8%
5	Chemicals and Allied Products	180	3.4%
6	Business Equipment	1639	31.2%
7	Telephone and Television Transmission	83	1.6%
8	Utilities	0	0.0%
9	Wholesale, Retail, and Some Services	660	12.6%
10	Healthcare, Medical Equipment, and Drugs	705	13.4%
11	Money Finance	973	18.5%
12	Other	280	5.3%
Total		5254	100%

This table shows the sample formation process (Panel A), sample distribution by year (Panel B) and by industry (Panel C). The industry classification is based on Fama-French 12 industries.

3.2. Media connections measure

We use the BoardEx database to determine managerial connections with *financial* media. Following prior studies (Gurun, 2020; Ru et al., 2020), we consider the following firms as 'Financial Media Firms': News Corporation, Bloomberg Media Group, The New York Times Company, Financial Times Group Ltd., NBC Universal (owns CNBC), Gannett Company (owns USA Today), Reuter Group plc., The Economist Group, Forbes Media LLC., Yahoo Finance Inc. In the next step, we identify all the directors, including all the executive directors or EDs (e.g., CEO, CFO) and non-executive directors or NEDs (e.g., Chairman, Vice-chairman), who have worked in these 'Financial Media Firms' and categorize them as 'Financial Media Directors'. After that, we use the director connection file in BoardEx to plot the connections of all the non-media firms in the BoardEx universe with the 'Financial Media Directors' identified in the previous step and denote each node as one media connection. These connections with media directors may have been established through prior employment, education, or social activities. We would like to note that most connections are established through prior employment. We ensure that the two individuals in a connection have an exact overlap of their tenure in a common firm/ university/ social institution. We also make sure that establishment of connection precedes media directors' role in a media firm. Once the connections are identified at the director level, we aggregate the media connections by firm-year. Finally, we construct the measure of financial media connection (*LOG_FIN_MC*) by taking the log of the number of media connections for a firm-year. Following is an example from our data to illustrate calculation of the financial media connection.

An employment connection has been established between Karl von der Heyden and Roy Burgess while both were working at PepsiCo. Their tenure at PepsiCo overlapped from 1996 to 1998. Later, Mr. Burgess served on the board of NBC Universal from 2004 to 2005. Therefore, we code Mr. Burgess as a 'financial media director' for the years 2004 and 2005. Though the connection between Mr. Heyden and Mr. Burgess was established in 1996, Mr. Burgess was linked to the media industry only for 2004 and 2005. Therefore, we code that Mr. Heyden has media connections for the years 2004 and 2005. Mr. Heyden's media connection then gets reflected in all the firms in which he worked in 2004 and 2005. Besides PepsiCo, Mr. Heyden worked at Macy's (1992–2010), DreamWorks Animation (2005–2009), May Department Stores (1992–2005), and Exult Inc. (2003–2004) in the years 2004 and/or 2005. While he also worked at Pitney Bowes (1966–1974), NYSE Euronext (2007–2008) and Huntington Ingalls Industries (2011–2016), his tenure at these firms were either before or after Mr. Burgess had media industry exposure. Therefore, these firms do not have media connection for the years 2004 and/or 2005 through Mr. Heyden.

We would like to point out that most of the media connections between non-media executives and financial media directors have formed in prior employment place, as shown in the anecdotal example above. The main assumption in calculating the measure is that the two individuals (i.e., non-media executive and media connection) have formed business or personal relationship while working together in the past. If the connection is formed through university, the assumption is that the two individuals attending the same university during the same period knew each other at the time. The limitation of this assumption is that the two individuals did not actually form any business or personal relationship despite working together in the same firm or attending the same university during the same time. These limitations work against our findings. Similar to other studies using this approach (e.g., Bhandari, Mammadov, Shelton, & Thevenot, 2018; Bruynseels & Cardinaels, 2014; Faleye et al., 2014; Javakhadze et al., 2016), readers should keep the limitations in mind when considering our results.

It is difficult to directly address these limitations given nature of the data. Therefore, we create alternative measures of media connections to demonstrate that our calculation of media connections variable is robust. Our inferences remain the same when we use these alternative measures of media connections: corporate executives use media connections to exacerbate analyst forecast optimism. We elaborate on this analysis in Section 5.3.

3.3. Empirical model

We use analyst forecast optimism to measure a firm's information environment. Analyst forecast optimism is the difference between annual forecasted earnings per share (EPS) and actual annual EPS divided by the stock price at time *t-1*. Thus, we use the following formula to calculate forecast optimism, which is consistent with prior studies (De Franco, Kothari, & Verdi, 2011; Engelberg et al., 2020; Lin et al. 2021; Coleman, Drake, Pacelli, & Twedt, 2022):

$$\text{Optimism} = \left[(\text{Forecast EPS}_t - \text{Actual EPS}_t)/\text{Stock Price}_{t-1}\right]^{*} 100$$

Surveying financial analysts, Orens and Lybaert (2010) determine that analysts use financial as well as non-financial information when forming their opinion, which suggests that their forecasts are likely to be affected by the biased media reports. Financial analysts respond to news

coverage by updating their research (Bradshaw et al., 2021; Frijns & Huynh, 2018). Bradshaw et al. (2021) determine that the quantity of news coverage is positively associated with analysts' recommendation revisions, primarily explained by qualitative rather than quantitative information in the news. These studies suggest that media outlets influence analysts' decisions. Forecast optimism (*OPTIMISM*) is the difference between actual annual earnings per share (EPS) and mean forecasted annual EPS scaled by the stock price at time *t-1* multiplied by 100.[4] The baseline model for our empirical analysis is shown in Eq. (1):

$$\begin{aligned} OPTIMISM_{it} =& \alpha_0 + \alpha_1 LOG\_FIN\_MC_{it} + \alpha_2 MED\_EXPERT_{it} + \alpha_3 SIZE_{it} \\ &+ \alpha_4 NSEGS_{it} + \alpha_5 GROWTH_{it} + \alpha_6 RD_{it} + \alpha_7 ADVERTISE_{it} \\ &+ \alpha_8 RET\_VOL_{it} + \alpha_9 SURPRISE_{it} + \alpha_{10} RET_{it} + \alpha_{11} LOSS_{it} \\ &+ \alpha_{12} HORIZON_{it} + \alpha_{13} ANALYST_{it} + \alpha_{14} IO_{it} + \alpha_{15} BIG4_{it} \\ &+ \alpha_{16} LNAUDIT_{it} + \alpha_{17} ROA_{it} + \alpha_{18} LEVERAGE_{it} \\ &+ Industry\ FE + Year\ FE + \varepsilon_{it} \end{aligned} \quad (1)$$

where *OPTIMISM* is analyst forecast optimism and *LOG_FIN_MC* is media connections for firm *i* in year *t*. A positive (negative) sign on *LOG_FIN_MC* would lend support to the manipulation (information efficiency) hypothesis.

3.4. Control variables

We include several control variables in our analyst forecast optimism model. In a recent study, Gurun (2020) determines that media expertise of board members generates more favorable media coverage and attribute it to the media-relations experience of the members. Therefore, we control for media expertise of board members (*MED_EXPERT*). We control for firm size (*SIZE*) as larger firms have a better information environment and less forecast bias. Following Lehavy, Li, and Merkley (2011), we control for the number of business segments (*NSEGS*) and firm growth (*GROWTH*) since firm complexity determines the analysts' effort. Intensity of intangible assets makes it difficult to analyze a firm. Therefore, we control for research and development (*RD*), and advertisement (*ADVERTISE*) expenses of the firm. Following prior literature such as Chang, Cho, and Shin (2007), and Bhandari, Mammadov, and Thevenot (2018), we control for volatility of the stock return (*RET_VOL*) and earnings surprise (*SURPRISE*). We control for stock return (*RET*) because it provides incentives for investors to follow the firm (Bhandari, Mammadov, & Thevenot, 2018). Next, we control for loss firms by including an indicator variable for these firms (*LOSS*) because it is difficult to predict the impact of losses (Behn, Choi, & Kang, 2008). We also control for the forecast horizon (*HORIZON*) as forecasts made closer to the earnings announcement date incorporate the most recent information (Behn et al., 2008). Next, we control for analyst following (*ANALYST*) because analyst coverage is closely associated with overall information environment and forecast bias (Behn et al., 2008; Bhandari, Mammadov, & Thevenot, 2018).

Institutional ownership is another factor that determines a firm's transparency and information production, which has implications for analysts' forecast characteristics (Boone & White, 2015). Therefore, we control for institutional ownership by calculating the ratio of shares held by institutional investors (*IO*). Abernathy, Kang, Krishnan, and Wang (2018) determine that auditors impact analysts' forecast characteristics, which is why we control for audit fee (*LNAUDIT*) and whether the company has a Big 4 auditor (*BIG4*). A firm's profitability is another factor that impacts analysts' forecasts (Cheng, Chu, & Ohlson, 2020), which is why we also control the firm's profitability (*ROA*). We include a firm's leverage ratio (*LEVERAGE*) to control for capital structure effects because it impacts analyst forecast characteristics (Mansi, Maxwell, & Miller, 2011). The industry-fixed effects included in Eq. (1) is based on Fama-French 49 industry classification. A detailed description of all variables is included in the Appendix.

[4] The results are qualitatively similar when we use the median forecasted EPS value.

Table 2
Descriptive statistics.

	N	Mean	Std Dev	Q1	Median	Q3
OPTIMISM	5254	0.358	0.714	0.043	0.129	0.343
RAW_FIN_MC	5254	1.606	2.521	0.000	1.000	2.000
LOG_FIN_MC	5254	0.677	0.689	0.000	0.693	1.099
MED_EXPERT	5254	0.100	0.299	0.000	0.000	0.000
SIZE	5254	7.762	1.514	6.685	7.678	8.804
NSEGS	5254	1.502	0.881	1.099	1.099	2.197
GROWTH	5254	1.069	0.142	1.007	1.054	1.115
RD	5254	0.012	0.063	0.000	0.000	0.000
ADVERTISE	5254	0.002	0.011	0.000	0.000	0.000
RET_VOL	5254	0.108	0.061	0.068	0.093	0.132
SURPRISE	5254	-0.004	0.280	-0.013	0.005	0.018
RET	5254	12.153	0.540	11.944	12.166	12.384
LOSS	5254	0.170	0.376	0.000	0.000	0.000
HORIZON	5254	5.077	0.122	5.023	5.113	5.115
ANALYST	5254	2.192	0.688	1.792	2.303	2.708
IO	5254	0.786	0.121	0.875	0.818	0.714
BIG4	5254	0.936	0.244	1.000	1.000	1.000
LNAUDIT	5254	14.463	0.974	13.790	14.382	15.143
ROA	5254	0.093	0.106	0.053	0.094	0.143
LEVERAGE	5254	0.505	0.250	0.334	0.498	0.643

This table shows descriptive statistics for the variables used in baseline regression analysis. All variables are defined in the Appendix. Continuous variables are winsorized at the 1st and 99th percentile.

4. Results

4.1. Descriptive statistics

Table 2 presents descriptive statistics of the variables that are used in eq. (1). All the continuous variables are winsorized at the top and bottom 1%. Firms have a mean (median) of 1.949 (2) financial media connections (*RAW_FIN_MC*). Analyst forecast optimism has a mean (median) of 0.356 (0.128) and vary from the first quartile of 0.042 to the third quartile of 0.341. Next, we turn to regression analysis to examine the effect of media connections.

4.2. Media connections and analyst forecast optimism

We estimate the regression analysis of analyst forecast optimism on media connections and control variables (Eq. 1) and report the results in Table 3. Each column presents a variation of the model specifications across different combinations of year, industry, year*industry, and firm-fixed effects. Thus, these results are robust and continue to hold whether we include year, industry, year-industry or firm-fixed effects. Coefficient estimates of *LOG_FIN_MC* are positive and statistically significant at 1 % level of significance across all specifications except column (6). These results provide preliminary support for the manipulation hypothesis. A positive coefficient on *LOG_FIN_MC* suggests that executives opportunistically use their financial media connections to increase analyst forecast optimism. The results further suggest that executives opportunistically use media connections to increase analyst forecast optimism because media is prone to bias and serving managers' interests. Managers may use their media connections to increase positive coverage about the firm, which we test in the next section. Our findings are consistent with prior studies demonstrating that executives opportunistically use their connections (Bruynseels & Cardinaels, 2014; Faleye et al., 2014; Khanna et al., 2015).

Table 3
Media connections and analyst forecast optimism.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	OPTIMISM	OPTIMISM	OPTIMISM	OPTIMISM	OPTIMISM	OPTIMISM
LOG_FIN_MC	0.031**	0.033**	0.042***	0.047***	0.051***	0.025*
	(2.111)	(2.242)	(2.648)	(2.842)	(2.920)	(1.798)
MED_EXPERT	−0.007	−0.012	−0.015	−0.020	−0.049	−0.005
	(−0.226)	(−0.373)	(−0.394)	(−0.541)	(−1.331)	(−0.085)
SIZE	−0.131***	−0.113***	−0.159***	−0.142***	−0.141***	−0.327***
	(−12.654)	(−10.297)	(−9.653)	(−8.292)	(−8.080)	(−6.728)
NSEGS	−0.006	−0.003	0.006	0.008	0.008	−0.035
	(−0.583)	(−0.256)	(0.519)	(0.632)	(0.651)	(−0.945)
GROWTH	−0.065	−0.113*	−0.082	−0.112	−0.099	0.057
	(−1.039)	(−1.755)	(−0.884)	(−1.160)	(−0.980)	(0.824)
RD	−0.067	0.014	0.045	0.115	0.181	0.223
	(−0.484)	(0.100)	(0.147)	(0.371)	(0.533)	(0.812)
ADVERTISE	−0.370	0.187	−0.322	0.256	0.113	−1.589
	(−0.477)	(0.240)	(−0.496)	(0.395)	(0.186)	(−1.622)
RET_VOL	2.232***	2.347***	2.104***	2.180***	2.259***	0.566*
	(13.345)	(12.686)	(8.220)	(7.595)	(7.168)	(1.965)
SURPRISE	−0.194***	−0.185***	−0.189*	−0.181	−0.129	−0.179
	(−6.210)	(−5.918)	(−1.657)	(−1.584)	(−1.160)	(−1.508)
RET	−0.176***	−0.162***	−0.170***	−0.157***	−0.155***	−0.091***
	(−10.369)	(−8.858)	(−4.974)	(−4.348)	(−4.295)	(−3.487)
LOSS	0.230***	0.236***	0.209***	0.215***	0.207***	0.116**
	(7.948)	(8.129)	(4.382)	(4.539)	(4.255)	(2.425)
HORIZON	−0.082	−0.078	−0.007	−0.011	−0.053	−0.029
	(−1.142)	(−1.075)	(−0.059)	(−0.090)	(−0.442)	(−0.275)
ANALYST	−0.011	−0.021	−0.024	−0.033*	−0.027	−0.036**
	(−0.713)	(−1.361)	(−1.292)	(−1.773)	(−1.476)	(−2.314)
IO	−0.085	0.043	−0.070	0.053	0.005	−0.179
	(−1.150)	(0.551)	(−0.699)	(0.507)	(0.049)	(−0.792)
BIG4	−0.130***	−0.119***	−0.122*	−0.111*	−0.126*	−0.178
	(−3.628)	(−3.310)	(−1.888)	(−1.724)	(−1.841)	(−1.549)
LNAUDIT	0.108***	0.084***	0.132***	0.109***	0.112***	0.117***
	(7.867)	(5.792)	(6.259)	(4.881)	(4.986)	(4.445)
ROA	−0.550***	−0.595***	−0.436**	−0.481**	−0.548**	−0.405
	(−5.405)	(−5.846)	(−2.050)	(−2.264)	(−2.476)	(−1.558)
LEVERAGE	0.296***	0.307***	0.253***	0.264***	0.245***	−0.015
	(8.194)	(8.447)	(3.942)	(3.945)	(3.758)	(−0.150)
Industry FE	No	No	Yes	Yes	No	No
Year FE	No	Yes	No	Yes	No	Yes
Industry FE * Year FE	No	No	No	No	Yes	No
Firm FE	No	No	No	No	No	Yes
adj. R-sq	0.266	0.272	0.292	0.296	0.308	0.443
N	5254	5254	5254	5254	5254	5254

This table reports results from the baseline regressions of analyst forecast optimism on media connections and control variables. The dependent variable is analyst forecast optimism (*OPTIMISM*), which is defined as the difference between actual earnings per share and mean forecasted EPS scaled by stock price at time t-1. The main independent variable is financial media connections (*LOG_FIN_MC*), which is estimated as the log of the number of financial media connections. All variables are defined in the Appendix. t-stats shown within parentheses are based on robust standard errors adjusted for heteroscedasticity and clustered by firm.

In terms of economic significance, when *LOG_FIN_MC* changes from 25th to 75th percentile, *OPTIMISM* increases by 15.66% of the sample mean.[5] Sign of coefficient estimates of the control variables are consistent with those of prior studies or not statistically significant. For example, larger firms have lower forecast optimism whereas firms with higher return volatility have higher forecast optimism. Coefficients for media expertise of board members (*MED_EXPERT*) are not statistically significant.

Our estimate of the media connection coefficient could be biased by common industry factors. As suggested by Gormley and Matsa (2014), we adjust for the industry effects by including industry * year-fixed effects in column (5) of Table 3 and the results are consistently significant.

Though we control for the common firm level determinants of forecast optimism, omitted variable bias may arise due to unobservable factors that are common across firms. We mitigate this concern by including firm-fixed effects in columns (6) of Table 3. Results show that the coefficient of *LOG_FIN_MC* is statistically significant (at 10 %) and positively related with *OPTIMISM*.

4.3. Underlying channel: Media coverage and sentiment

In this section, we examine whether media coverage is an underlying channel of the relation between media connections and forecast optimism. Our preliminary results are consistent with the manipulation hypothesis, which argues that managers tend to exploit their connections in the media firms to achieve favorable media coverage, which in turn, is likely to misguide the analysts in producing more optimistic earnings forecasts. As Solomon (2012) suggests that it is easier to spin non-earnings announcement news compared to earnings announcement news, we argue that media connection is likely to affect the soft information rather than the hard information. Furthermore, Bradshaw et al. (2021) show that qualitative rather than quantitative information in the news primarily explains the effect of news coverage on analysts' recommendations. Therefore, evidence that media connected firms receive more media coverage, and a more positive tone in the coverage, would validate the argument that the effect of media connections on analyst

[5] We use the following formula to measure the economic significance of the results: {Coefficient (LOG_FIN_MC) x [75th percentile (LOG_FIN_MC) – 25th percentile (LOG_FIN_MC)]}/ Mean (OPTIMISM). For the analyst forecast optimism model: [0.051*(1.099–0)]/0.358 = 15.66%.

forecast optimism is channelled through media coverage. This mediation analysis would provide further support to the manipulation hypothesis. To test this conjecture, we examine whether media coverage is an underlying channel of the relation between media connections and forecast optimism.

Using Sobel (1982) methodology and following recent studies (Murphy & Sandino, 2020; Wu, Peng, Shan, & Zhang, 2020), we employ a three-equation model to test the mediating role of media coverage and sentiment on the relationship between information environment and media connections.

$$OPTIMISM_{it} = \alpha_0 + \alpha_1 LOG\_FIN\_MC_{it} + \sum Controls_{it} + Industry\ FE + Year\ FE + \varepsilon_{it} \quad (2)$$

$$LOG\_NEWS_{it}(SENT_{it}) = \beta_0 + \beta_1 LOG\_FIN\_MC_{it} + \sum Controls_{it} + Industry\ FE + Year\ FE + \varepsilon_{it} \quad (3)$$

$$OPTIMISM_{it} = \gamma_0 + \gamma_1 LOG\_FIN\_MC_{it} + \gamma_2 LOG\_NEWS_{it}(SENT_{it}) + \sum Controls_{it} + Industry\ FE + Year\ FE + \varepsilon_{it} \quad (4)$$

Coefficient of *LOG_FIN_MC* (α_1) estimates the overall effect of media connections on forecast optimism in eq. (2). Then, coefficient of *LOG_FIN_MC* (β_1) in eq. (3) denotes the effect of media connections on media coverage (*LOG_NEWS*). Finally, coefficient of *LOG_FIN_MC* (γ_1) in eq. (4) shows the direct effect of media connections on forecast optimism after controlling for the mediating variable (i.e., media coverage). In addition to media coverage, we also use media sentiment (*SENT*) as a separate mediator and estimate the same three-equation model. Following Baron and Kenny (1986), media coverage would be considered a mediator if both α_1 and β_1 coefficients are statistically significant. Then a statistically significant γ_1 coefficient would indicate a partial mediation, while an insignificant γ_1 would infer full mediation. Such mediation analysis is widely used in literature to examine the underlying channel of influence. Some recent studies that use mediation analysis include Gimbar, Hansen, & Ozlanski, 2016, Murphy & Sandino, 2020, Wu et al., 2020 among others.

We construct measures of media coverage and media sentiment using Bloomberg data, following Ben-Rephael, Da, and Israelsen (2017) and Hossain and Javakhadze (2020). We annualize the Bloomberg variable *NEWS_HEAT_PUB_DNUMSTORIES,* which is the number of news articles about a company published on a given day, by taking sum of all daily observations. Our news coverage variable (*Log_NEWS*) is the natural logarithm of the sum of daily number of news articles published about the company in each year. To capture news sentiment, we use the Bloomberg variables NEWS_SENTIMENT_DAILY_MAX (ranges from 0 to 1) and NEWS_SENTIMENT_DAILY_MIN (ranges from −1 to 0). First, we divide NEWS_SENTIMENT_DAILY_MAX by the negative of NEWS_SENTIMENT_DAILY_MIN so that this ratio represents overall sentiment at daily level. Then we average the daily sentiment measure over the year to annualize it and name it as our news sentiment measure, *SENT*.

We report results of the mediation analysis in Table 4. Sample size is much smaller in this table compared to Table 3 due to the inclusion of media coverage and sentiment variables, which are not available for some firms. Despite the smaller sample size, the *LOG_FIN_MC* coefficient (α_1) in column (1) is still positive and statistically significant at 5 % significance level. Then columns (2) and (4) show results of eq. (3) and we observe that both media coverage (*LOG_NEWS*) and sentiment (*SENT*) are positively associated with *LOG_FIN_MC*. These results suggest that media connection is related with not only more news coverage but also more positive news sentiment, which are consistent with the media bias theory documented in prior studies (Gurun & Butler, 2012; Hossain & Javakhadze, 2020; Ru et al., 2020).

Columns (3) and (5) show results of eq. (4). Results indicate that inclusion of media coverage (*LOG_FIN_NEWS* in column 3) reduces the effect of media connections on forecast optimism since the coefficient estimate of *LOG_FIN_MC* becomes smaller in size. The *LOG_FIN_MC* coefficient is 0.055 in column (1) and 0.038 in column (3), where the coefficient also loses statistical significance at the 5 % level. This result implies that media connections affect information environment through media coverage. In column (5), we do not see any mediation effect of news sentiment (*SENT*) because the coefficient of *LOG_FIN_MC* does not change in magnitude and statistical significance relative to that of Column (1). In column (6), we include both media coverage (*Log_NEWS*) and sentiment (*SENT*) as mediating variables. Results suggest that media connections increase forecast bias through both media coverage and sentiment. Overall, mediation analysis demonstrates that company insiders use media connections to increase forecast bias through news coverage and sentiment, which is again consistent with our manipulation hypothesis.

4.4. Additional analysis

In this section, we conduct several cross-sectional analyses to shed further light on the relation between media connections and forecast optimism.

4.4.1. Do managerial incentives moderate the effect of media connection?

Based on the manipulation hypothesis, we expect that managerial incentives would moderate the relation between media connection and forecast optimism. Miller (2006) states that the stock prices of companies are sensitive to the news cycle. Negative media coverage causes a stock price decline and increases volatility (Fang & Peress, 2009). Therefore, we argue that the managers whose wealth is more closely associated with performance of stock price volatility will have a greater incentive to increase forecast optimism.

Following Kannan, Skantz, and Higgs (2014), we use the average vega of executives' equity portfolio as a proxy for managerial equity incentives.[6] Vega measures the sensitivity of the executives' equity portfolio to changes in volatility of the stock price. We calculate vega of the equity portfolio of the top five executives.[7] This proxy captures the incentives of the executives tied to the stock price volatility of the firm. We follow Core and Guay (2002) methodology to calculate vega of the executives' equity portfolio. A higher value of vega suggests a stronger incentive for corporate executives. We create an indicator variable High VEGA that equals one for higher than sample median values, and zero otherwise.

Table 5 column (1) shows the result of the cross-sectional analysis of managerial incentive. Coefficient of the interaction term *High VEGA* * *LOG_FIN_MC* is positive and statistically significant at 5 % level. This analysis suggests that company executives are more likely to increase forecast optimism if they have higher equity incentives, lending further support to the manipulation hypothesis.

4.4.2. Do managers use media connection in lieu of strict monitoring and earnings management?

Numerous studies document that stricter board oversight increases monitoring of financial reporting and makes it difficult for company managers to engage in opportunistic financial reporting, thereby enhancing a firm's information environment (e.g., Armstrong, Guay, & Weber, 2010). Klein (2002) determines that more independent boards restrict earnings management activities, and Frankel, McVay, and

[6] Kannan et al. (2014) conclude that auditors perceive the vega of executives' portfolio as a risk factor but do not find statistically significant results for delta. Therefore, we use vega to measure the incentives of executives.

[7] The ExecuComp database, from which we obtain the equity compensation data, includes information for only the top five executives of a firm. Although this measure does not directly capture the equity incentives of the executive directors, it is still a strong proxy for estimating the equity incentives of the directors.

Table 4
Underlying channel: media coverage and sentiment.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	OPTIMISM	LOG_NEWS	OPTIMISM	SENT	OPTIMISM	OPTIMISM
LOG_FIN_MC	0.053**	0.141***	0.039**	0.111*	0.053**	0.038**
	(2.466)	(4.186)	(3.267)	(1.881)	(2.456)	(3.174)
LOG_NEWS			0.101***			0.101***
			(6.318)			(6.258)
SENT					0.004	0.002
					(0.762)	(0.482)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
adj. R-sq	0.326	0.785	0.335	0.086	0.326	0.335
N	2451	2451	2451	2451	2451	2451

This table presents the mediating effect of news coverage on the relationship between analyst forecast optimism and media connections. Analyst forecast optimism (*OPTIMISM*) is defined as the difference between actual earnings per share and mean forecasted EPS scaled by stock price at time t-1. *OPTIMISM* is the dependent variable in columns (1), (3), (5), and (6). The main independent variable is financial media connections (*LOG_FIN_MC*), which is estimated as the log of the number of financial media connections. The two mediating variables are *LOG_NEWS* and *SENT*. *LOG_NEWS* is the log of one plus the number of news articles published in a year. *SENT* is the average sentiment of news articles published in a year. All variables are defined in the Appendix. t-stats shown within parentheses are based on robust standard errors adjusted for heteroscedasticity and clustered by firm.

Table 5
Additional analysis: managerial incentive, board independence, and earnings management.

	(1)	(2)	(3)
Dependent Variable	OPTIMISM		
LOG_FIN_MC	0.057*	0.021	0.015
	(1.736)	(0.779)	(0.574)
High VEGA	0.103		
	(1.574)		
High VEGA * LOG_FIN_MC	**0.047****		
	(1.974)		
High INDEP		−0.132**	
		(−2.304)	
High INDEP * LOG_FIN_MC		**0.054*****	
		(2.602)	
Low EM			−0.137*
			(−1.870)
Low EM * LOG_FIN_MC			**0.051***
			(1.705)
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
adj. R-sq	0.351	0.264	0.377
N	2017	1780	1059

This table reports cross-sectional analysis of the relation between analyst forecast optimism and media connections by managerial incentive, board independence, and earnings management. The dependent variable is analyst forecast optimism (*OPTIMISM*), which is defined as the difference between actual earnings per share and mean forecasted EPS scaled by stock price at time t-1. The main independent variable is financial media connections (*LOG_FIN_MC*), which is estimated as the log of one plus the number of financial media connections. *HIGH VEGA* is an indicator variable, which is 1 for greater than median values of average delta of the executives, 0 otherwise. *HIGH INDEP* is an indicator variable, which is 1 for greater than median values of board independence, 0 otherwise. *LOW EM* is an indicator variable, which is 1 for lower than median values of discretionary accruals, 0 otherwise. All variables are defined in the Appendix. t-stats shown within parentheses are based on robust standard errors adjusted for heteroscedasticity and clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1%, respectively.

Soliman (2011) conclude that more independent boards are associated with a better information environment. In contrast, some studies document that executives use their connections to circumvent rules and avoid oversight of the independent board members (e.g., Bruynseels & Cardinaels, 2014; Khanna et al., 2015). This view implies that the firms with a stricter board monitoring are more likely to use media connections to increase forecast optimism because independent boards make it difficult to engage in other types of opportunistic financial reporting, such as earnings management.

To investigate the role of board monitoring and earnings management, we estimate our model again and control for the impact of board monitoring. We use the percentage of independent board members to measure the board monitoring. Using board independence data from IRRC Risk Metrics database, we create an indicator variable High INDEP that equals one for higher than sample median values, and zero otherwise. We use Kothari, Leone, and Wasley (2005) performance-adjusted discretionary accruals to measure earnings management. Indicator variable *Low EM* equals one for the firm-year observations with lower than sample median discretionary accruals, and zero otherwise.

Table 5 columns (2) and (3) report the results of our estimations. The interaction of *High INDEP * LOG_FIN_MC* is positive and statistically significant (*coef.* = 0.50; *t-stat* = 2.54), suggesting that company insiders are more likely to leverage their media connections to increase forecast optimism in the presence of strict board monitoring.

Next, coefficient of the interaction term *Low EM * LOG_ FIN_MC* in Table 5 column (3) is positive and statistically significant (*coef.* = 0.060; *t-stat* = 2.02), which reveals that the negative effect of media connection on forecast optimism is more pronounced for the firms with lower level of earnings management. Our interpretation is that managers use their media connections to achieve manipulation of soft information when it is difficult to engage in earnings management.[8] Results reported in columns (4) and (5) of Table 5 suggest that media connections exacerbate analyst forecast optimism for the firms with a better information environment, measured using firm size (column 4) and analyst coverage (column 5). These results further demonstrate that managers rely more on media connections to spin positive story about the company when traditional governance mechanisms prevent opportunistic behavior.

In summary, results in Table 5 suggest that corporate managers tend to exploit media connections to increase forecast optimism in the presence of strict board monitoring. Results also suggest that media connections could be used to manufacture soft information in lieu of earnings management.

5. Robustness tests

In this section, we perform several robustness analyses to demonstrate that our baseline results are robust. We provide a detailed

[8] Cohen, Dey, and Lys (2008) empirically demonstrate that engaging in real earnings management is one mechanism that companies employ in lieu of accruals based earnings management.

discussion below.

5.1. Sub-sample analysis and alternative industry classification

The 2008 financial crisis gives an opportunity to investigate whether our results are driven by the new regulatory environment. To ensure that the financial crisis does not affect our results, we exclude all observations during the financial crisis period (years 2008 and 2009) and re-estimate our baseline analysis. As reported in Table 6 panel A column 1, our results remain qualitatively similar. The 2008 financial crisis enacted a paradigm shift in regulatory environment, which may have implications for analysts' forecast behavior. To mitigate concerns regarding the possible impact of these changes, we divide the sample into two subsamples: Table 6 panel A column 2 (3) shows the results for the sample covering the years between 1999 and 2007 (2010 and 2014). The results across the two different samples are qualitatively similar to the baseline results. Next, we re-estimate our baseline model and use 2-digit SIC codes industry classification instead of Fama-French 49 industry classification and report the results in Table 6 panel A column 4. Coefficient estimates are consistent across all specifications, demonstrating further robustness of our results.

5.2. Alternative dependent variables

In this section, we use alternative dependent variables to demonstrate that the results are not biased by the choice of analyst forecast bias measure. We also use the analyst forecast dispersion, for which a higher value of dispersion suggests a lower-quality information environment (Bhandari, Mammadov, Shelton, & Thevenot, 2018; Bhandari, Mammadov, & Thevenot, 2018). The analyst forecast dispersion is the standard deviation of analyst earnings forecasts, scaled by the stock price at the end of the fiscal year. Our results, reported in Table 6 panel B column 1, suggest that the firms with larger media connections are more likely to manipulate information environment, which increases analyst forecast dispersion. In addition, we use the market-based proxy to capture the information environment to demonstrate that the results are not sensitive to the choice of alternative information environment proxies. The bid-ask spread is another measure of the information environment, which is based on the stock price of the company, and is widely used in studies to assess the quality of the information environment (Callahan, Lee, & Yohn, 1997; Frankel & Li, 2004). Similar to Yoon, Zo, & Ciganek (2011), we use the following formula to measure the bid-ask spread:

$$\text{Bid-Ask Spread} = \frac{\text{Ask Price–Bid Price}}{[(\text{Ask Price} + \text{Bid Price})/2]}$$

where a higher value for relative spread suggests a lower-quality information environment. We multiply the relative spread by 100, similar to the forecast optimism measure. Results reported in Table 6 panel B under columns 2 (*SPREAD*) and 3 (*LOG_SPREAD*) suggest that the firm with larger media connections have lower information environment.

5.3. Alternative independent variables

We would like to note that our inferences remain the same when we use three alternate definitions of our independent variable. First, we consider a restricted measure of media connection in which we calculate media connections with only journalists and editors. These results are reported in Table 6 panel C under column 1. Inferences remain the same: firms with larger number of connections with journalists and editors have higher analyst forecast bias.

Second, we use an indicator variable for the media connections measure, which takes a value of 1 for firms that have media connections greater than the sample median, and zero otherwise. Third, following Faleye et al. (2014), we use a detrended measure of media connection. Mechanical time trend in social network data is likely to bias coefficient

Table 6
Robustness tests.

Panel A: Subsample Analysis and Alternate Industry Classification

	(1)	(2)	(3)	(4)
	Exclude Financial Crisis period	Pre-financial crisis	Post-financial crisis	SIC2 Industry FE
Dependent Variable	OPTIMISM	OPTIMISM	OPTIMISM	OPTIMISM
LOG_FIN_MC	0.040**	0.039*	0.044**	0.047***
	(2.551)	(1.833)	(2.021)	(2.801)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
adj. R-sq	0.250	0.243	0.280	0.301
N	4296	1888	2408	5254

Panel B: Alternate Dependent Variables

	(1)	(2)	(3)
Dependent Variable	DISPERSION	SPREAD	LOG_SPREAD
LOG_FIN_MC	0.015**	0.011**	0.038**
	(2.302)	(1.964)	(2.195)
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
adj. R-sq	0.243	0.526	0.767
N	3242	5263	5263

Panel C: Alternate Independent Variables

	(1)	(2)	(3)
Dependent Variable	OPTIMISM	OPTIMISM	OPTIMISM
LOG_FIN_MC_ED_JOURN	0.045***		
	(2.893)		
FIN_MC_DUMMY		0.069***	
		(2.834)	
LOG_FIN_MC_DETREND			0.080***
			(2.706)
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
adj. R-sq	0.296	0.297	0.297
N	5254	5254	4728

This table reports results from the robustness tests. Panel A, B and C reports results from subsample analysis, models with alternate dependent variables, alternate independent variables, respectively. In panel A, column (1) reports results for a subsample that excludes observations for the years 2008 and 2009. Column (2) shows results for the pre-crisis sub-period, and Column (3) reports results for the post-crisis sub-period. Column (4) shows results for the models run with SIC2 digit industry-fixed effects. The dependent variable, *OPTIMISM*, is defined as the difference between actual earnings per share and mean forecasted EPS scaled by stock price at time t – 1. In panel B, alternate dependent variables are used. These alternate dependent variables are *DISPERSION*, defined as the standard deviation of analyst earnings forecasts, scaled by the stock price at time t – 1; *SPREAD*, defined as the ratio of difference between ask and bid price scaled by the average of ask and bid price; and *LOG_SPREAD,* which is the natural logarithm of *SPREAD*. In panel A and B, the main independent variable is financial media connections (*LOG_FIN_MC*), which is estimated as the log of one plus the number of financial media connections. In panel C, alternate independent variables are used. LOG_FIN_MC_ED_JOURN is the log of one plus the number of financial media connections that are restricted to connections with editors and journalists; FIN_MC_DUMMY is an indicator variable, which is 1 for firms that has media connections greater than the sample median, 0 otherwise; LOG_FIN_MC_DETREND is the detrended media connection measure calculated by regressing raw media connections measure on a time variable and then taking the natural log of 1 plus the sum of the residual and the absolute value of its sample minimum. All variables are defined in the Appendix. t-stats shown within parentheses are based on robust standard errors adjusted for heteroscedasticity

and clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1%, respectively.

estimates. Therefore, we create a detrended measure by regressing raw media connections measure on a time variable. Then we calculate the detrended media connection measure as the natural log of 1 plus the sum of the residual and the absolute value of its sample minimum. Results of these alternate independent variables are reported in Table 6 panel C under columns 2 and 3. We find that our baseline results continue to hold, suggesting that our inferences are robust across alternate definitions of media connections.

We also conduct additional robustness for the mediation analysis, where we replace analyst forecast optimism with analyst forecast dispersion and bid-ask spread. Untabulated results suggest that inferences remain the same: managers use their media connections to generate more news coverage about their firm and sentiment of the coverage is more optimistic. This distorts a firm's information environment, which is why analyst forecast dispersion and bid-ask spread is higher.

6. Endogeneity concerns

In this section, we perform a battery of tests to address potential endogeneity concerns that may arise in the relationship between media connections and information environment.

6.1. Propensity score matching

To address the problem of non-random selection, we employ propensity score matching (PSM) method. Since our media connection measure is continuous, we create an indicator variable *Indicator_MC*, which equals one for the top quintile of media connection and zero for the bottom quintile of media connection. We estimate logistic regression of eq. (1) using *Indicator_MC*. We use propensity scores to match (without replacement) firms in the top quintile of media connections with firms in the bottom quintile of media connection for each year. This procedure provides reasonable assurance that firms with higher media connections (treated sample) are paired with firms that have lower media connections (control sample) with statistically similar characteristics. To assess covariate balance between the treatment and control groups, we report both *t*-test of the difference in mean between the two groups.

Table 7 reports the results of the propensity score matching approach. In Panel A of Table 7, we compare the firm characteristics of the treated and control samples. t-test of differences in means show that there is no statistical difference among characteristics of the treated and control samples. In Panel B of Table 7, we show results of the regression analysis for the matched sample. Coefficients of *Indicator_FIN_MC* and *LOG_FIN_MC* are positive and statistically significant in all specifications as reported in columns (1) and (2) of Table 7- panel B.

In addition, we also perform matching through entropy balancing method following Hainmueller (2012) and Wilde (2017). While the conventional PSM method results in a much smaller sample (604 versus 5526 in the main model), the entropy balancing method helps overcome this limitation. Entropy balancing method weights observations on a continuous scale instead of assigning a weight of one or zero. The method facilitates optimal weighted match with treatment observations, achieving covariate balance while retaining the original sample (5526 observations) size to improve efficiency in tests (Chapman, Miller, & White, 2019; Wilde, 2017). To create entropy balanced sample, we define media connection indicator variable as one for above sample median firms, and zero otherwise. Table 7 Panel B columns (3) and (4) show results from the entropy balancing method. We find that results are qualitatively similar in these specifications as well.

Table 7
Propensity score matching.

Panel A: Comparison of Covariates between Treated and Control samples

	HIGH_FIN MC (*N* = 287)	LOW_FIN MC (N = 287)	Difference	t-stat
SIZE	7.805	7.804	0.001	0.0072
NSEGS	1.532	1.478	0.054	0.7444
GROWTH	1.060	1.064	−0.004	−0.467
RD	0.012	0.01	0.002	0.6188
ADVERTISE	0.002	0.002	0.000	0.4774
RET_VOL	0.106	0.103	0.003	0.5417
SURPRISE	−0.0213	0.0265	-0.0478*	−1.807
RET	12.131	12.155	−0.024	0.6715
LOSS	0.169	0.162	0.007	0.2186
HORIZON	5.078	5.073	0.005	0.4452
ANALYST	2.199	2.164	0.035	0.6155
IO	0.787	0.773	0.014	1.4592
BIG4	0.967	0.940	0.027	1.5487
LNAUDIT	14.533	14.260	0.273***	3.548
ROA	0.095	0.107	−0.012	−1.5987
LEVERAGE	0.545	0.499	0.046***	2.1485

Panel B: PSM and Entropy-Balanced Sample Regressions

	(1)	(2)	(3)	(4)
Dependent Variable	OPTIMISM	OPTIMISM	OPTIMISM	OPTIMISM
FIN_MC_DUMMY	0.143**		0.060***	
	(2.466)		(3.279)	
LOG_FIN_MC		0.069**		0.039***
		(2.073)		(3.007)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
adj. R-sq	0.307	0.304	0.269	0.268
N	574	574	5254	5254

This table shows results for the propensity score matching approach. Panel A shows the comparison of covariates across the treated sample (high financial media connection firms) and the control sample (low financial media connection firms). Treated and control samples are created based on the indicator variables, *FIN_MC_DUMMY*, which takes a value of 1 (0) if media connection is greater than the sample median. Panel B, columns (1) and (2) reports regression results for the propensity score matched sample. Panel B columns (3) and (4) shows regressions results from the sample created by the entropy balancing approach. In all specifications, the dependent variable is analyst forecast optimism (*OPTIMISM*), which is defined as the difference between actual earnings per share and mean forecasted EPS scaled by stock price at time t-1. The main independent variable is financial media connections (*LOG_FIN_MC*), which is estimated as the log of one plus the number of financial media connections. All variables are defined in the Appendix. t-stats shown within parentheses are based on robust standard errors adjusted for heteroscedasticity and clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1%, respectively.

6.2. Difference-in-difference analysis

We estimate difference-in-difference analysis around the turnover of media connected executives. Similar to Hossain and Javakhadze (2020), we exploit the departure of media connected executives as a shock to firms' media connection. Following Gormley and Matsa (2011), we construct a cohort of treatment and control firms for the three years before (t - 3) and after (t + 3) the turnover events. Since it is possible for a firm to have multiple turnover events during our sample period, we remove the events that are less than 3 years apart from each other.

We consider each year as a cohort and assign a firm into treatment (control) group if it has experienced at least one (zero) turnover in a year. Then for each cohort a treatment-control pair is identified by estimating the probability of a firm being treated using logistic regression analysis of eq. (1). We match each treated firm-year observation to a control firm-year observation based on Fama-French 49 industry, and closest propensity score. Once the cohorts are created, we estimate the following regression:

$$OPTIMISM_{it} = \alpha_0 + \alpha_1 TREAT_i + \alpha_2 POST_t + \alpha_3 Treat_i{*}POST_t + Control_{it} + Industry\ FE + Year\ FE + \varepsilon_{it} \quad (5)$$

where *TREAT* equals one for the treatment observations, and zero for the control observations. *POST* is an indicator variable that equals one (zero) for the three years after (before) a turnover event for both the treatment and the control firms.

Table 8 reports results of the difference-in-difference regressions. Coefficient estimates of *POST* × *TREAT* are negative and statistically significant at 5 % level, suggesting that analyst forecast optimism declines following the departure of media connected executives. In other words, reduction in media connections caused by the turnover of media connected executives leads to a less biased analyst forecast. Overall, this evidence is consistent with implications of the manipulation hypothesis.

6.3. Instrumental variable estimation

We assess the possibility of reverse causality, where forecast optimism may influence firms to appoint media connected executives so that they alleviate information asymmetry by news dissemination through their connections. To overcome this challenge, we use the number of media firms near the firm's headquarters as our instrumental variable. Our instrument is plausibly an exogenous shock to media connections since a firm's headquarter location is pre-determined and likely to be associated with the firm's social connectedness with media. However, it is not likely that proximity will have a direct effect on analyst forecast optimism. Our approach is analogous to that of Garcia-Feijoo, Hossain, and Javakhadze (2021) and Di Giuli and Laux (2022).

Table 9 presents results of the instrumental variable estimation. First stage results are reported in columns (1) and (3), and second stage results are in columns (2) and (4). We see that media connection is positively associated with the number of media firms located within the same county as the firm's headquarter. Using the predicted media connection (*PRED_LOG_FIN_MC*) from the first stage of the two-stage least square (2SLS) model, we estimate eq. (1) by replacing *LOG_FIN_MC* with the predicted number of media connections obtained from the first stage. Results of the second stage regressions are qualitatively similar to our baseline results in Table 3, which shows a positive relation between media connection and forecast optimism. We also observe that the F-test (28.97) of excluding instruments is much higher than the cut-off value of 10, indicating that our instrument is relevant and does not suffer from weak-instrument concerns. Furthermore, test of exogeneity shows that media connection variable is endogenous in our specification. Therefore, results from the instrumental variable estimation lend further credibility to the main findings that media connections increase analyst forecast optimism.

Table 8
Difference-in-difference analysis.

	(1)	(2)	(3)
Dependent Variable	OPTIMISM	OPTIMISM	OPTIMISM
POST	0.100***	0.094***	0.083**
	(2.743)	(2.609)	(2.114)
TREAT	0.014	0.017	0.021
	(0.374)	(0.465)	(0.571)
TREAT * POST	−0.105**	−0.102**	−0.108**
	(−2.076)	(−2.043)	(−2.150)
Controls	Yes	Yes	Yes
Industry FE	No	Yes	Yes
Year FE	No	No	Yes
adj. R-sq	0.234	0.262	0.262
N	1763	1762	1762

This table shows results from the difference-in-difference analysis around the turnover of financial media connected executives. By identifying the years in which firms have experienced turnover of at least one media connected executive, we define *TREAT* as 1 for the turnover experiencing firms and 0 for all other firms. Considering each year as a cohort, each treatment firm is matched with a control firm based on year, industry, and closest propensity score. Then *POST* is defined as 1 (0) for the 3 years following (preceding) the turnover event for both the treatment and control firms in a pair. All variables are defined in the Appendix. t-stats shown within parentheses are based on robust standard errors adjusted for heteroscedasticity and clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1%, respectively.

Table 9
Instrumental variable estimation.

	(1)	(2)
	1st Stage	*2nd Stage*
Dependent Variable	LOG_FIN_MC	OPTIMISM
Log_FINMEDIA_FIRM	0.062***	
	(4.160)	
Pred_LOG_FIN_MC		0.737*
		(1.680)
Controls	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
N	5017	5017
F-test of excluding instruments	26.36	
Test of Endogeneity statistic	0.19	
[*p*-value]	0.66	

This table reports results from 2-SLS IV regressions. In Stage 1, Media Connection (*LOG_FIN_MC*) is instrumented by the log of 1 plus the number of financial media companies located in the same county as the firm's headquarter (*Log_FINMEDIA_FIRM*). In Stage 2, *OPTIMISM* is regressed on predicted financial media connection (*Pred_LOG_FIN_MC*). Analyst forecast optimism (*OPTIMISM*) is defined as the difference between actual earnings per share and mean forecasted EPS scaled by stock price at time t-1. Financial media connections (*LOG_FIN_MC*) is estimated as the log of one plus the number of financial media connections. All variables are defined in the Appendix. t-stats based on clustered standard errors in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1%.

7. Conclusion

We investigate the effect of having friends in media on analyst forecast optimism. Prior studies on executives' connections demonstrate that they may use their connections to benefit the firm. Related literature shows the opposite findings; company insiders use their connections opportunistically to benefit themselves to the detriment of shareholders. Our study empirically examines and finds that corporate insiders use their media connections to increase analyst forecast optimism. We call this the manipulation hypothesis. Cross-sectional analysis suggest that company insiders are more likely to use media connections to increase forecast optimism in presence of stronger board monitoring. Our results are consistent across a battery of tests that address endogeneity issues and robustness tests.

Our findings have significant policy implications as promoting transparency in financial journalism could ensure that investors receive unbiased analyst forecasts. Policymakers should closely monitor the social connections between corporate executives and the media to gauge the potential influence of such connections on analyst forecasts. Increased transparency in disclosing these connections can help mitigate bias and ensure that investors receive unbiased forecasts from the analysts. Furthermore, media outlets should be encouraged to adopt ethical guidelines that promote transparency of corporate reporting by journalists. This includes disclosing all sorts of relationships with corporations to maintain credibility of the media outlet. These policy implications are likely to strike a balance between the need for open information flow and the importance of maintaining the integrity and objectivity of financial journalism. By addressing the potential influence of media connections on analyst forecasts, policymakers can contribute to fair and transparent financial markets that benefit investors as well as the broader economy.

Our study can be extended in several ways. A potential avenue for future research is to analyze the effects of social media connections on analyst forecast optimism. Social media is gaining popularity, including among the investing community. Therefore, it would be interesting to investigate how social media connections affect analyst forecasts.

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Declaration of competing interest

None.

Data availability

The authors do not have permission to share data.

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Appendix A

Dependent Variables	
OPTIMISM	Difference between actual annual EPS and mean forecasted annual EPS, scaled by the stock price at the end of the fiscal year. We multiply the measure by 100;
Independent Variables	
LOG_ FIN_MC	We consider the following firms as 'Financial Media Firms': News Corporation, Bloomberg Media Group, The New York Times Company, Financial Times Group Ltd., NBC Universal (owns CNBC), Gannett Company (owns USA Today), Reuter Group plc., The Economist Group, Forbes Media LLC., Yahoo Finance Inc. We identify all the directors who have worked in these 'Media Firms' and categorize them as 'Financial Media Directors'. After that, we use the director connection file in BoardEx to plot the connections of all the non-media firms in the BoardEx universe with the 'Financial Media Directors' identified in the previous step and denote each node as one media connection. Financial media executives are currently working in media firms. These connections with media directors may have been established through prior employment, education, or social activities (most connections are established through prior employment). We ensure that the two individuals in a connection have an exact overlap of their tenure in a common firm/ university/ social institution. Once the connections are identified at the director level, we aggregate the media connections by firm-year. Finally, we construct the measure of financial media connection by taking the log of the number of media connections for a firm-year;
Indicator_MC	An indicator variable that takes a value of 1 for the top quintile of media connection, and 0 for the bottom quintile of media connection;
Control Variables	
MED_EXPERT	An indicator variable of 1 if a firm has at least one director who has prior experience of working in a financial media firm, and zero otherwise. Financial media firms are identified under *LOG_ FIN_MC*;
SIZE	Logarithmic transformation of market value;
NSEGS	Logarithmic transformation of number of segments;
GROWTH	Market-to-book ratio, calculated as the market value scaled by the book value of the firm;
RD	Research and development expense scaled by sales;
ADVERTISE	Advertising expenses scaled by total assets;
RET_VOL	Standard deviation of daily return over the last fiscal year;
SURPRISE	Difference between current earnings per share and prior year earnings per share, scaled by the stock price of the firm;
RET	Annual stock return calculated;
LOSS	An indicator variable of 1 if earnings before extraordinary items is less than zero, and zero otherwise;
HORIZON	Logarithmic transformation of the average number of calendar days between mean forecast announcement date and subsequent actual earnings announcement date;
ANALYST	Logarithm transformation of the number of analysts following the firm;
IO	Ratio of the shares held by institutional investors;
BIG4	An indicator variable of 1 if the firm employs one of the big 4 auditors, and zero otherwise;
LNAUDIT	Logarithmic transformation of the audit fees;
ROA	Net income scaled by total assets;
LEVERAGE	Long term debt scaled by total assets;
Other Variables	
BOARD_INDEP	Total number of independent board members in the company scaled by the total number of directors;
EM	Absolute value of discretionary accruals following Jones (1991) and modified by Kothari et al. (2005) using performance-matched measure;
Log_MEDIA_FIRM	Logarithmic transformation of the number of media firms located within the 3-digit zip code of the firm;
Log_NEWS	Logarithm transformation of the number of news articles of a company during a fiscal year;
SENT	Average daily sentiment measure over a year. Daily sentiment is estimated as the absolute value of the ratio of NEWS_SENTIMENT_DAILY_MAX (ranges from 0 to 1) to NEWS_SENTIMENT_DAILY_MIN (ranges from −1 to 0).

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