Does Media Sentiment on Target Innovation Predict Performance of Technology Mergers and Acquisitions?

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Acknowledgments:

*We thank Yanjian Zhu, Maobin Wang, and seminar participants at the 2021 (4th) China Finance Scholar Forum and the 2022 (6th) China Accounting and Finance Conference, 2023 World Finance Conference, Zhejiang University, University of International Business and Economics, for very helpful comments and suggestions. All errors are our own. Yugang Chen would like to thank National Social Science Fund of China(approval numbers 23AZD021), National Natural Science Foundation (NNSF) of China (approval numbers 71972191, 72132010, U1811462).

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Abstract

Media plays a crucial intermediary role in disseminating innovations and arising the public awareness. But little is known in extant literature about how to measure media sentiment of innovation and its impact on corporate investments like acquiring technology via mergers and acquisitions (M&As). In this study, we self-construct a text-based measure for media sentiment of innovation (*MedSI*) reflecting a target's innovation productivity as reported in news released around the M&A announcements and find it predicts superior short-term post-announcement performance in Chinese technology M&As. We further dissect *MedSI* into its expected component (*MedPred*) and unexpected component (*MedBias*) and reveal that the positive impact on short-term post-announcement performance is primarily attributed to *MedPred*, especially when overall market investor sentiment or attention is strong. Moreover, *MedPred* demonstrates the ability to predict superior long-term post-announcement performance and innovation productivity. These findings remain robust in identification checks and various tests involving subsamples and alternative measures.

Keywords: media sentiment of innovation, technology M&As, media bias

JEL codes: G34, Q55, L82

1. Introduction

In the last two decades, high-technology firms have gained significant prominence in the economy (Fedyk et al., 2017), and investors have displayed substantial interest in companies offering promising new technologies (Shiller, 2017). The pursuit of new technologies and innovative solutions often compels firms to expand their resources and capabilities through mergers and acquisitions (M&As) (Makri et al., 2010). Technology M&As have evolved into a well-established corporate phenomenon that garners extensive attention from investors (Uhlenbruck et al., 2006).[1] However, assessing the impact of target firms' innovation on acquirers has proven challenging for investors due to their general lack of professional knowledge in determining the scientific and economic value of innovation (Kogan et al., 2017). This challenge is even more pronounced in technology M&As in emerging markets, such as China, where individual investors are the primary participants (Titman et al., 2022), M&A transparency is low (Bushman et al., 2004), and nearly all M&As involve private or subsidiary targets (Borochin & Cu, 2018).[2] These factors collectively create difficulties for investors in gathering and interpreting information about target firms' innovation productivity in technology M&As.

Media is expected to play a crucial intermediary role in reducing the information asymmetry faced by investors in technology M&As. As outsiders, investors usually cannot rely on internal disclosures for useful information regarding the proposed M&As, and private targets are often even more opaque than the acquiring companies (Borochin & Cu, 2018). Except for firsthand experience or personal communication, nearly all information received by investors undergoes an external process, typically involving the media (Ahern & Peress, 2022).

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[1] Uhlenbruck et al. (2006) focus on the acquisitions of resources and capabilities by acquiring Internet (online) firms, which are defined as technology M&As in their study. Our definition of technology M&As is detailed later in the introduction.
[2] Bushman et al. (2004) define M&As transparency as the widespread availability of M&As-specific information to those market participants outside acquirers and targets.

Investors usually turn to the media to access information about target firms' innovation productivity in technology M&As. While media content can be viewed as an informative measure of a stock's value that mitigates information asymmetry between firms and investors (Bushee et al., 2010; Tetlock et al., 2008), media could also gauge investor sentiment and amplify investor bias (García, 2013). It remains unclear whether media content enables investors to make more informed investment decisions (Engelberg, 2018). Even though media facilitates spreading awareness about innovations and generates interest in new products or ideas, no prior research has considered measuring such innovation sentiment conveyed via media as an information intermediary. In particular, extant literature offers little insight on whether and how sentiment of the targets' innovation conveyed in media affects the performance in technology M&A despite the importance of the targets' innovation in such transactions.

We try to fill the void of the literature by examining whether and how media sentiment of innovation, defined as the overall attitude, opinion, or tone expressed by the media toward the innovation productivity of target companies around M&A announcements, predict superior post-announcement performance in technology M&As. We investigate this research question in China because of its prominent role in redrawing the global innovation map.[3] The media's coverage of Chinese technology M&As, amidst the competing demands of various stakeholders, also provides a fascinating informational backdrop for examining our research question. Building on prior research, we define a transaction as a technology M&A in China if it meets one of the following three criteria: 1) the primary motivation disclosed in the M&A announcement is to acquire the target's knowledge base (Ahuja & Katila, 2001); 2) the M&A occurs in the high-tech industry as classified by the Chinese National Bureau of Statistics in

[3] The 2022 edition of the Global Innovation Index (GII) ranks China as 11th among 132 economies by total innovation score – the highest score received by any country not in the high-income category.

2017 (Makri et al., 2010); and 3) the target possessed at least one valid invention patent before the M&A (Han et al., 2018).[4] Our empirical investigation explores whether media sentiment of innovation (*MedSI*), a self-constructed text-based measure reflecting the extent of innovation productivity related to the target reported in media, has an impact on post-announcement performance, yielding corroborative evidence. An increase in *MedSI* by one standard deviation results in an average abnormal return of 3.02% during the 5-day window surrounding M&A announcements.

To delve deeper into our research question, we follow the methods of Huang et al. (2014) and Lott and Hassett (2014) by conducting regressions of *MedSI* against the target's fundamentals, which encompass aspects like innovation productivity, financial performance, and risk. This enables us to break down *MedSI* into its expected portion (*MedPred*, a prediction from linear regression) and its unexpected portion (*MedBias*, the residual from linear regression). *MedPred* reflects media opinions influenced by the acquirer's and the target's fundamentals, while *MedBias* could represent media's independent opinions or biases. We proceed to examine the two components of *MedSI* on post-announcement performance and find that both have short-term effects. However, only *MedPred* exerts a significant influence on the long-term post-announcement performance in technology M&As.

To explore the causal nature of these associations, we employ an instrumental variable (IV) approach adopted in You et al. (2018), utilizing the introduction of a high-speed rail between the cities of a firm's headquarter and a newspaper's headquarter. This introduction reduces journalists' onsite visiting costs, enhances their awareness of target firms' innovation activities, and diminishes information asymmetry between the media and firms. The 2SLS IV

[4] Makri et al. (2010) use M&As in high-tech industry as technology M&As because high-tech industry is knowledge-intensive industries that use science in the development of inventions. Ahuja and Katila (2001) suggest that technology M&As can be viewed as an absorption of the acquired firm’s knowledge base into the acquiring firm’s knowledge base. Han et al. (2018) classify M&As in which the target firm had applied for at least one patent in the 5 years prior to M&As are considered technological M&As.

regression results corroborate our baseline findings. In summary, the identification tests suggest that *MedSI* has a significant causal effect on post-announcement performance in technology M&As. Our results remain robust across a battery of further tests involving subsamples and an alternative measurement of *MedSI*.

Subsequently, we explore the moderating impact of market-level investor sentiment and investor search volume concerning a company's innovation activities. We find that investors with more optimistic sentiment or a higher level of interest in a company's innovation activities are more responsive to *MedSI*, *MedPred*, and *MedBias* overall. However, only the effect of *MedPred* is significant in our subsequent tests evaluating whether *MedSI* predicts the target's post-announcement innovation. This indicates that fundamentals, rather than the media's independent opinions, forecast the target's innovation productivity.

Our study contributes primarily to the burgeoning literature on textual analysis of corporate innovation (Bellstam et al., 2021; Chu et al., 2023; Mukherjee et al., 2017). Previous research on innovation has typically relied on proxies constructed from research and development (R&D) expenditure (e.g., Chan et al., 2001) or patent counts (e.g., Lerner & Seru, 2022). Mukherjee et al. (2017) create measures of new product announcements through textual analysis of press releases by media regarding new products. We conduct textual analysis of press releases by media regarding the innovation potential of technology M&A targets. Chu et al. (2023) discover that greater innovation disclosure in new product announcements predicts favorable future sales and a more positive market reaction. Unlike their focus on managerial voluntary non-financial disclosure of new product innovation, our empirical analysis accounts for the sentiment of innovation in M&A announcements, managerial mandatory disclosure of innovation, that disseminate information about technology value of common interest among technology peers (Cai et al., 2024). Intriguingly, we find that managerial announcement sentiment of innovation has a significantly negative impact on the long-term post-announcement performance in technology M&As, suggesting that managers may tend to exaggerate the innovation productivity of target firms in M&A announcements. Bellstam et al. (2021) introduced a measure of innovation using textual analysis of analyst reports for S&P500 firms. Our study adopts a word-dictionary approach of textual analysis and diverges from Bellstam et al. (2021) in assessing the information intermediary's evaluation of the target firms' innovation potential rather than their innovation success. Inspired by Bellstam et al. (2021), we also construct a text-based measure of innovation noted as “analyst sentiment of innovation” using analyst reports and control it in our analysis of the impact of *MedSI* on the post-announcement performance in technology M&As. Our findings suggest that analyst sentiment of innovation has a limited effect on the post-announcement performance in technology M&As. Contributing to this line of literature, we construct media sentiment of innovation and find it more evident compare with managerial sentiment of innovation revealed in M&A announcements or analyst sentiment of innovation found in analyst reports on technology M&As.

Moreover, we contribute to the existing literature that examines the information intermediary role of media news.[5] The well-established causality between media content and market reaction is widely acknowledged (Tetlock, 2015). Even in the absence of introducing new information, newspapers can facilitate information dissemination and aid investors in comprehending a firm's fundamentals (e.g., Boulland et al., 2017; Drake et al., 2014; Guest, 2021).[6] Our research delves into the information intermediary role of media coverage regarding the innovation capabilities of private target firms in technology M&As. We introduce

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[5] An information intermediary is defined in Bushee et al. (2010) as an agent providing information that is new and useful to other parties because it has neither been publicly released nor widely disseminated.
[6] It is also a common argument in that information reported in media is hardly new. Prior to appearing on newspapers, information may have already appeared via internet, television, government reports or corporate announcements. Investors trade on stale information, implying that they are more likely to be impacted by the salience(e.g., Tetlock, 2011), bias or slant (e.g., Gurun & Butler, 2012)of news rather than new information (e.g., Dyck et al., 2010).

a novel distinction between media sentiment of innovation tied to fundamentals and media-biased sentiment by decomposing *MedSI* into *MedPred* and *MedBias*, as afore explained. We provide robust empirical evidence that *MedPred* predicts both short-term and long-term post-announcement performance in technology M&As, while *MedBias* only has a short-term effect.

Finally, our study contributes to the emerging literature on media sentiment in M&A transactions (Liao et al., 2021; Yang et al., 2019), which finds that positive media sentiment before M&A announcements predicts positive stock returns and deal premiums. While these prior studies analyze the media sentiment of publicly listed acquirers, our research focuses on the media sentiment of private target firms in technology M&As, adjusting for the media sentiment of the public acquirer. In this vein, we offer novel empirical evidence indicating that media sentiment regarding the private target firms itself also predicts positive post-announcement performance, at least in the short-term.

The remaining sections of our paper are outlined as follows: Section 2 introduces the institutional background. Section 3 offers a summary of the relevant literature and outlines the hypotheses. Section 4 details the sample, data, and research design. Section 5 investigates the impact of *MedSI* on post-announcement performance. Section 6 delves into the measurement of media sentiment prediction (bias) of innovation and examines its effect on post-announcement performance. Section 7 presents the results of robustness checks and endogeneity tests. Section 8 serves as the conclusion.

2. Institutional Backgrounds

2.1. M&As in China and their Comparability with those in Developed Markets

M&As in China have experienced a rapid growth since 2000, driven by the country's economic transformation and development. They differ significantly from those in developed markets, primarily in terms of poor transparency and a prevalence of private firms as targets, rather than public firms.

M&As within the Chinese stock market are characterized by poor transparency. Despite the potential benefits of transparency in terms of development, information disclosure in China is the result of competing incentives, both in favor of and against transparency. Factors such as concentrated ownership structures, weak legal systems, highly politicized institutional arrangements, rent-seeking behavior, and corruption often tip the scale in favor of opacity, outweighing the advantages of market-driven transparency (Piotroski & Wong, 2012). Consequently, despite recent institutional and regulatory improvements, the Chinese stock market continues to grapple with weak information systems and low-quality information. This lack of transparency, coupled with weak government regulation, allows acquirers to divert resources away from shareholders in M&As (Yang et al., 2019).

Almost every M&A deal in the Chinese stock market involves a private or subsidiary target (Borochin & Cu, 2018). For instance, a striking 96.2% of publicly listed acquirers in China choose to acquire private or subsidiary targets, a significantly higher proportion than the corresponding figure of 76.8% in the U.S. from 2009 to 2019.[7] This phenomenon aligns with Shleifer and Vishny's (2003) explanation that, even in the absence of synergy, Chinese publicly listed firms prefer private targets mainly due to overvaluation by acquirers and opportunities for merger arbitrage.[8] Given that virtually all M&As involve private or subsidiary targets, individual investors, who constitute a major portion of participants in the Chinese stock market (Titman et al., 2022), have limited access to public information regarding conventional M&As

[7] See the abstract of "Valuation Arbitrage and M&A: Evidence from Chinese Companies". https://x.cnki.net/kcms/detail/detail.aspx?dbcode=CJFD&dbname=CJFDTEMP&filename=JJGU201903006&v=jnHFUZH%mmd2BEvQcATEH4o8fdnt7nMX1QANpUcpW6wgMkyu5IUafy5fJg%mmd2Bn0A8XsM4mO

[8] Under tight constraints of China Securities Regulatory Commission (CSRC), market values of small, listed firms in China include a substantial component related not to the firm's underlying business but instead to these companies' potential to be shells in reverse mergers. Although CSRC launched a pilot program on March 31, 2010, by gradually removing the short sales ban on certain firms, investors still have a limited ability to short stocks. These contribute to the overvaluation of M&A deals in China.

and private targets in China.[9] This restriction contributes to price discovery challenges and facilitates mispricing (Qian, 2014) of M&As, further exacerbating the issue of overvaluation in M&A deals in China.

As conventional M&As in China differ significantly from those in developed markets, our paper focuses exclusively on technology Material Asset Reorganizations (MARs) which correspond to large technology M&As in developed markets, and we refer to them as technology M&As throughout our paper. In practice, the China Securities Regulatory Commission (CSRC) categorizes mergers into two distinct groups: conventional M&As and MARs. The CSRC imposes strict approval requirements and mandates mandatory information disclosure for MARs but not for conventional M&As. Due to the absence of mandatory information disclosure, conventional M&As do not align with the characteristics of medium and small M&As seen in developed markets. According to CSRC regulations, a M&A is classified as an MAR if it meets one of the following three criteria: first, the total assets acquired by the acquirer account for over 50% of its year-end total assets, as stated in the audited consolidated financial statement for the latest fiscal year. Second, the revenue generated from the assets acquired by the acquirer in the latest fiscal year constitutes over 50% of its total revenue, as reported in the audited consolidated financial statement for the same period. Last, the net assets acquired by the acquirer account for over 50% of its year-end net assets, as indicated in the audited consolidated financial statement for the latest fiscal year, and the value of the acquired net assets exceeds 50 million RMB. Consequently, the MARs defined in the Chinese market are of a much larger magnitude and are more comparable to the large M&As observed in developed markets compared to conventional M&As.

[9] In Chinese stock market, individual investors have access to acquirers' fundamentals from "annual report" within four months of the end of each fiscal year, "interim report" within two months following the end of the first half of each fiscal year, and "quarterly reports" within one month following the end of a given quarter. All annual reports are required to be audited by a qualified Chartered Public Accountant (Piotroski and Wong, 2012). However, individual investors hardly have access to private targets' fundamentals since private firms rarely publish these reports because of auditing costs and trade secrets.

Considering the recognized deficiencies in the corporate governance of listed firms (Jiang et al., 2010), investors cannot rely on internal disclosures of information pertaining to proposed technology M&As. The combination of poor technology M&A transparency and the fact that virtually all M&As involve private or subsidiary targets leaves investors with limited or no access to public details about private targets of M&As in China. Therefore, individual investors must turn to alternative sources, like media, to obtain information about M&As and private targets in the Chinese stock market. Consequently, media plays a crucial informational role in Chinese M&As, providing a valuable research context for examining whether the media empowers investors to make more informed investment decisions.

2.2. Role Played by Media in M&As in China

The demand for information disclosure increased after China joined the World Trade Organization in 2001 due to the shift toward a market-based business model. However, government control over the media has adapted rather than diminished (Borochin & Cu, 2018). Simultaneously, media outlets may lean toward positive reporting to maintain relationships with their advertising clients (Gurun & Butler, 2012). In terms of reporting content, Chinese media finds itself in a challenging position, needing to cater to the preferences of corporate clients, the market's demand for accurate reporting, and the government's regulatory requirements (Borochin & Cu, 2018).

Chinese media faces the challenging task of meeting the diverse demands of the market for accurate coverage, as well as those of the government and corporate sectors for favorable coverage (Borochin & Cu, 2018). Media outlets may have preferences regarding the actions investors should take, and these preferences can arise from both external and internal incentives within the media industry (Puglisi & Snyder, 2015). Presently, China features a mix of state-controlled media and progressive market-oriented media. Chinese media outlets may strive to meet investor demands for accurate coverage and provide more comprehensive information about a firm's fundamentals (You et al., 2018). However, China's government conglomeration reform has given the government more political control over the media, resulting in a more positive tone in official newspaper articles (Piotroski et al., 2017).[10] Local media also has incentives to provide favorable coverage to local firms, driven by pressures related to local advertising (Gurun & Butler, 2012) or social connections (Hossain & Javakhadze, 2020). Overall, while Chinese media must address the demands of both the government and corporate entities for favorable coverage, a causal relationship is evidenced between media content and market reaction in China (e.g., Borochin & Cu, 2018; You et al., 2018). Hence, media plays a critical role in disseminating and interpreting information in the Chinese stock market (You et al., 2018).

3. How Media Sentiment of the Target Firm's Innovation May Affect Post-Announcement Performance in Technology M&As?

Innovation has been recognized as a value-creating factor in M&As, with acquiring innovation representing a significant motive behind such transactions (Bena & Li; Phillips & Zhdanov, 2013). Large and mature firms often seek to bolster their R&D capabilities by acquiring smaller, innovative firms (Phillips & Zhdanov, 2013). Prior research investigating the role of innovation in technology M&As has primarily relied on indicators such as R&D expenses and patented innovations. For instance, Bena and Li (2014) found that firms with more patents are less likely to become acquisition targets, but those with higher R&D expenses and less growth in patenting are more likely to be acquired. However, relying solely on patents and R&D expenditures may underestimate the significance of innovation. Recently, a few

[10] "Conglomeration is a media reform that orchestrates the organization of existing official and nonofficial newspapers from the same locality into a single commercialized news group. Although foreign competition (as a result of China joining the World Trade Organization) is often cited as a reason for forming news groups (Lee et al., 2006), the government's real intention behind conglomeration is to retain strong political control over the press while allowing it to pursue market objectives." (Piotroski et al. 2017, page 180)

studies have pioneered the use of textual analysis to measure innovation. Chu et al. (2023) employed a word-dictionary textual analysis of managerial narratives in new product announcements to gauge innovation disclosure, finding correlations with future sales performance and market reactions. Bellstam et al. (2021) developed a measure of innovation using a fitted latent Dirichlet allocation model, allowing for 15 distinct topics, and demonstrated that descriptions of corporate innovation in the text of analyst reports capture genuine innovation. Textual analysis offers an opportunity to explore how the market reacts to corporate innovation information disclosed by media and other participants in the stock market.

The causal relationship between media coverage and market reactions has received thorough examination in prior literature. Typically, media coverage of a firm leads to an increase in its trading volume and volatility compared to days when it remains absent from media attention (Tetlock 2010). Firms that garner more media coverage tend to experience lower ex-post returns (Fang & Peress, 2009). Furthermore, the sentiment expressed in media articles, as determined through textual analysis, predicts returns in the subsequent days, following the same sentiment direction (Tetlock et al. 2008). Given that financial media both caters to and influences investors' beliefs and biases (Mullainathan & Shleifer, 2005), media sentiment has been employed as a proxy for investor sentiment in recent studies. Some of these studies delve into the impact of media sentiment on managerial and firm behaviors, including areas such as accounting or corporate frauds (Dyck et al. 2010), corporate governance (Dyck et al., 2008), and executive compensation (Kuhnen & Niessen, 2012).[11] Others document the effects of media news on asset pricing in various scenarios, including Initial Public Offerings (IPO) (Cook et al., 2006), seasoned equity offerings (Sun et al., 2020), bubbles (Bhattacharya

[11] While most these studies examine the impact of media sentiment on corporate or managerial decision, Wu and Tian (2021) show that firms can spend more public relation expenditure to reduce a negative pre-IPO media tone and through such media capture, firms can influence regulatory decisions. For example, an IPO firms with less negative media tone is more likely to be approved by the financial authority.

et al., 2009), and recessions (García, 2013).

However, despite its vital role in generating and disseminating information related to M&As, prior research on the impact of media sentiment on M&A transactions is rather limited with only two studies focusing on the media sentiment of acquirers. Yang et al. (2019) examined whether pre-merger news about acquirers correlates with M&A performance and found that a positive media attitude before M&A announcements in the U.S. has predictive power for stock returns in both the short and long terms. Liao et al. (2021) offered cross-country evidence that media sentiment of acquirers could influence their acquisition decisions, finding that firms with more positive media sentiments are more likely to become acquirers and to offer higher deal premiums.

To the best of our knowledge, no prior study has explored the media sentiment of innovation in general and for target firms in technology M&A transactions in particular. Investigating the media sentiment of private target firms in M&As is significant because media news plays a crucial role in providing information about the targets' fundamentals to equity market participants, supplementing information from other intermediaries and public sources (Tetlock et al. 2008). Media sentiment can be seen as an informative indicator of a stock's value, reducing the information asymmetry between firms and investors (Tetlock et al. 2008). Additionally, as mentioned earlier, the information content provided by media sentiment of private target firms is less likely to replicate other public information in the Chinese stock market.

In contributing to the research on media sentiment in M&A transactions, our study examines *MedSI* concerning target firms in technology M&As. We argue that such *MedSI* may convey valuable information about the target's innovation productivity, encompassing aspects like scientific or economic value, thereby aiding investors in assessing the impact of the target's innovation on acquirers. Naturally, media outlets in China may have incentives to align with government and acquirer demands and report favorably on the target's innovation productivity. Regardless of whether *MedSI* provides incremental information related to target fundamentals or simply reflects the nature of technology deals, it is likely to predict superior post-announcement performance, at least in the short-term. Based on these premises, we hypothesize that media sentiment influences investors' expectations regarding the acquirer's expected present discounted value of cash flows, i.e., stock price, around the announcement of technology M&As, as outlined in our first hypothesis.

H1: *High media sentiment of innovation (MedSI) predicts superior post-announcement performance in technology M&As.*

We then employ linear prediction to decompose *MedSI* into two components: media sentiment prediction and bias of innovation. Media sentiment prediction of innovation may reflect the media's opinions generated by the target's fundamentals, such as performance, risk (Renneboog & Vansteenkiste, 2019), and innovation productivity (Sevilir and Tian 2012).[12] If media sentiment prediction of innovation primarily mirrors the media's opinions based on the target's fundamentals, we anticipate that high media sentiment prediction of innovation, resulting from strong target fundamentals, will predict superior post-announcement performance in both the short-term and long-term. This forms the basis for our next hypothesis.

H2: *High media sentiment prediction of innovation (MedPred) predicts superior post-announcement performance in technology M&As in both the short-term and long-term.*

Market responses to media releases of information, as examined in previous literature, are influenced not only by the information content view but also the investor sentiment view (Tetlock 2015). Unlike the information content view, the investor sentiment view posits that

[12] Renneboog and Vansteenkiste (2019) suggest that target's performance (risk) is positively (negatively) related to short-term and long-term performance. Sevilir and Tian (2012) find that acquiring innovative target with existing patents is positively related to acquirer abnormal returns at announcement as well as acquirer's long-term stock return performance after deal completion.

media content can induce, amplify, or reflect investor interpretations of stock market performance that appear unjustified by fundamentals(Tetlock, 2007). Investor sentiment, characterized by biased investor beliefs, impacts M&A transactions (e.g., Shleifer and Vishny 2003). Consequently, media sentiment bias of innovation may reflect the media's subjective opinions or bias, which are not supported by the target's fundamentals. During the M&A negotiation period, media coverage may even be manipulated by managers, resulting in news stories unrelated to acquirers' fundamentals and capable of generating only a short-term increase in bidders' stock prices (Ahern & Sosyura, 2014). If the media provides a favorably biased description of the target's innovation productivity based on its own preferences, investors may eventually realize the degree of bias during the post-acquisition period.[13] We present an anecdotal case in Appendix 1 and develop a theoretical model of media sentiment bias of innovation in relation to technology M&As in Appendix 2. Any positive *MedSI* regarding the target's innovation productivity that appears unjustified by fundamentals may induce optimistic investor sentiment, resulting in high short-term post-announcement performance but having no impact on long-term performance. Consequently, media sentiment bias of innovation is likely to trigger a short-term market reaction, leading to our final hypothesis below.

H3: *High media sentiment bias of innovation (MedBias) predicts superior post-announcement performance in technology M&As in the short-term but not in the long-term.*

4. Research Design, Sample, and Data

4.1. Regression Models and Variable Measurement

In testing the first hypothesis, *H1*, we develop the following regression model to

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[13] Counter intuitively, Carpenter et al. (2021) find that stock prices in China have become as informative about future profits as those in the US.

investigate the relationship between *MedSI* and short-term post-announcement performance:

$$CARs_i = \alpha_0 + \alpha_1 MedSI_i + \alpha_2 Controls_i + Year_i + Industry_i + \varepsilon_i \quad (1)$$

where, the dependent variable is the acquirer's cumulative abnormal returns (*CARs*), calculated following the standard event study methodology. We estimate abnormal returns using the Fama-French Three-factor model (Fama & French, 1993). We consider T_5 (if a M&A deal is suspended) or T_4 (if a M&A deal is not suspended), as shown in Figure 1, as the 0th day, select the [−5, +5] event window, and use the 250 trading days preceding the event window as the estimation window.[14]

The primary independent variable of interest in Model (1), *MedSI*, is a self-constructed text-based measure. To create this measure, we first compile a list of keywords related to innovation from media reports, following the "word-list" approach widely used in previous studies (Bellstam et al., 2021; Chu et al., 2023; Merkley, 2014).[15] These keywords are categorized into those associated with innovation investment, cooperation, outcome, and generalization. Subsequently, we calculate the innovation keyword ratio by dividing the number of keywords related to the target's innovation productivity by the total number of words (in thousands) in a media report. This ratio is then multiplied by the sentiment score of the media report, which is calculated as the difference between negative and positive words used in each report, scaled by their total count (Loughran & Mcdonald, 2011). Finally, we compute the average value of these ratios across all reports for each sample technology M&A.[16]

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[14] Our empirical results remain robustness using alternative estimation windows for [−2, +2], [−3, +3] or [−10, +10] days.

[15] Please refer to Appendix 4 for our innovation keywords list. Merkley (2014) examine how earnings performance relates to firms' narrative R&D disclosure decisions in annual reports and measure the quantity of narrative R&D disclosures as the number of R&D-related sentences in the 10-K filings of firms. Bellstam et al. (2021) measure innovation by counting the number of "innovative words" in each document scaled by the length of the document. Chu et al. (2023) measure innovation disclosure as the natural logarithm of one plus the number of innovation words in a new product announcement.

[16] It is the innovation description of news, rather than sentiment of news, which drives our results. Use sentiment-adjusted measure can avoid this case: if one news is talking with neutral or negative sentiment about the target, it is less likely that the strong innovation description of news reflects stronger innovation capability by the target. The innovation keywords ratio and the sentiment of news have a low correlation equal to 0.262***. Thus, the innovation description of news is unlikely to have same information with the sentiment of news. Further, as robustness exercises, we use the innovation keywords ratio, and we have also controlled for sentiment of news. In each case, the results are robust.

In Model (1), we also control for analyst sentiment of innovation (*AnaSI*), which is calculated at the technology M&As level in a manner similar to the measurement of *MedSI*. Initially, we determine the innovation keyword ratio for analyst reports by dividing the number of keywords related to the target's innovation productivity by the total number of words (in thousands) in each analyst report. This ratio is then multiplied by the sentiment score of the analyst report. Finally, we calculate the average of these values across all analyst reports for each sample technology M&A.

Furthermore, we account for M&A announcement sentiment of innovation in Model (1). Within M&A announcements, the Purpose of Transaction (POT) section articulates why the acquirer is pursuing the transaction, while the Target's Competitive Advantages (TCA) section outlines the advantages of the target over its competitors. Both sections can provide valuable information about the target's innovation productivity. To calculate M&A announcement sentiment of innovation (*AnnSI*), we first determine the innovation keyword ratio by dividing the number of innovation-related keywords by the total number of words (in thousands) and then multiply it by the sentiment score for each of the POT and TCA sections. Additionally, we calculate M&A announcement sentiment of innovation using only the POT Section (*AnnSIP*) and only the TCA Section (*AnnSIC*) for robustness checks.

Multivariate regression Model (1) includes several control variables that have been associated with merger outcomes in prior studies. We control for acquirers' firm characteristics, such as size (*Size_Acq*), ROA (*ROA_Acq*), market-to-book ratio (*MB_Acq*), liquidity (*Liq_Acq*), leverage ratio (*Lev_Acq*), pre-M&As stock returns (*RunUp_Acq*) (Furfine & Rosen, 2011), age (*Age_Acq*) (Nguyen & Phan, 2017), and state-owned status (*SOE_Acq*) (You et al., 2018). We further account for the acquirers' governance (Hossain & Javakhadze, 2020) by including the acquirers' board size (*BrdSize_Acq*), independence size (*IndSize_Acq*), and the shareholding ratio of the largest shareholder (*Top1_Acq*). Additionally, we control for target characteristics

(Sevilir & Tian, 2012), including the target's pre-announcement granted invention patent counts (*IP*) or utility patent counts (*UP*).[17] Deal characteristics comprise dummy variables for deals financed with equity (*Equity*) and the ratio of deal value to acquirers' market value as relative size (*RelVal*).

Assessing bias in a relatively objective, replicable, and cost-effective manner presents a challenging task, despite widespread belief in its existence (Puglisi & Snyder, 2015). Previous research has attempted to estimate bias using the residuals of linear models that controls for fundamental factors to estimate the biased disclosure due to tone management (Huang et al. 2014) or political bias in newspaper coverage of economic events (Lott and Hassett 2014). Inspired by this approach, we run regressions between *MedSI* and acquirer's and target's fundamentals. We measure the predicted media sentiment of innovation as *MedPred* and the regression residuals as *MedBias*. We then develop Model (2) to test the hypotheses *H2* and *H3* regarding the impact of media innovation prediction and bias on short-term post-announcement performance.

$$\begin{aligned} CARs_i &= \beta_0 + \beta_1 MedPred_i + \beta_2 MedBias_i + \beta_3 Controls_i \\ &\quad + Year_i + Industry_i + \varepsilon_i \end{aligned} \tag{2}$$

As aforementioned, *MedPred* and *MedBias* are measured from Model (3), which examines the linear relationship between *MedSI* and acquirer's and target's fundamentals:

$$MedSI_i = \beta_0 + \beta_1 Factors_i + \beta_2 Controls_i + Year_i + Industry_i + \varepsilon_i \tag{3}$$

where the dependent variable *MedSI* is calculated at the technology M&As level. The independent variables (*Factors*) include acquirer's and target's fundamentals, such as acquirer's size (*Size_Acq*), ROA (*ROA_Acq*), market-to-book ratio (*MB_Acq*), liquidity (*Liq_Acq*),

[17] The patent application process in China is comparable to that of the U.S. and Europe although China generally has a poor record and significant variations across regions on intellectual property rights protection and local enforcements. Despite its limitations), patent count is correlated with R&D input and financial output and can be meaningful indicators for innovation. Following prior studies on the innovations of Chinese firms, we use patent count as the proxy for innovation productivity of the target firms of technology M&As in China.

leverage ratio (*Lev_Acq*), target's ROA (*ROA_Tar*), target's pre-announcement granted invention patent counts (*IP*) or utility patent counts (*UP*), leverage ratio (*Lev_Tar*), size (*Size_Tar*), and Tobin's q (*TobinQ_Tar*), as per prior studies (Borochin and Cu 2018, Hossain and Javakhadze 2020).[18] Year-fixed effects and industry fixed effects are controlled for in all regressions, and robust standard errors are used.

For testing hypotheses *H2* and *H3*, we also introduce the following regression models (4) and (5) to investigate the relationship between *MedSI* and long-term post-announcement performance:

$$BHARs_i = \alpha_0 + \alpha_1 MedSI_i + \alpha_2 Controls_i + Year_i + Industry_i + \varepsilon_i \tag{4}$$

$$\begin{aligned} BHARs_i = \beta_0 + \beta_1 MedPred_i + \beta_2 MedBias_i + \beta_3 Controls_i \\ + Year_i + Industry_i + \varepsilon_i \end{aligned} \tag{5}$$

We calculate the 12-month buy-and-hold abnormal returns (*BHARs*) following Lyon et al. (1999) for each acquirer using two benchmarks for expected returns: the returns of the 25 value-weighted, non-rebalanced portfolios grouped by both firm size and book-to-market ratio, and the returns of the 25 equally-weighted, non-rebalanced portfolios grouped by both firm size and book-to-market ratio.

4.2. Sample and Data

We manually extracted the MARs announcements made by A-share listed firms from June 2008 to December 2021 from the Cninfo database that covers the Shanghai Stock Exchange and Shenzhen Stock Exchange.[19] Our sample period commences in June 2008, following the announcement of the first MAR subsequent to the implementation of the Detailed Rules for

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[18] Targets only publish brief financial statements in M&A announcements because of trade secrets protection or unaudited financial data. Due to missing data, we can only collect some target characteristics. Because most of the targets are unlisted firms in China stock market and there is no public data for targets, we manually collect data from M&A announcements. The calculate methods of target characteristics are consistent with those used to calculate acquirer's characteristics.

[19] Cninfo belongs to Shenzhen Stock Exchange and is the only website legally qualified for multi-level capital market information disclosure in China. http://www.cninfo.com.cn/. In Section 2, we explained the reasons to focus on the technology MARs and refer to them as technology M&As in our paper.

M&As of Listed Firms (Order of CSRC No. 53) in May 2008. The final MAR in our dataset was announced in December 2021. We excluded the technology M&As announced after this date, as our analysis focuses on the impact of MedSI on up to one-year post-announcement performance, i.e., for a sample technology M&A announced in 2021, we need to collect its stock market performance information in 2022.

The timeline of a technology M&A's process and the definition of the media reporting period are illustrated in Figure 1. After negotiations between the acquirer and the target, the acquirer often applies for a trading suspension. In our sample, 93.57% of technology M&As involved such a suspension. If the acquirer experiences a trading suspension, we define the period from the framework agreement to the resumption of trading as the media reporting period. However, if the acquirer is not subject to a trading suspension, we define the period to the announcement as the media reporting period.

(Insert Figure 1 about here)

We screened the data in accordance with established M&A research practices and manually collected 2,407 media reports covering 498 technology M&As announced between June 2008 and December 2021. The screening criteria and process are detailed in Panel A of Table 1. As illustrated in Panel B of Table 1, the final sample spans various industries, with the majority originating from the manufacturing sector. As such, our study expands the coverage of technology M&As beyond the scope of previous research, which predominantly focused on internet companies (Uhlenbruck et al., 2006), the telecommunications industry (Ransbotham & Mitra, 2010), and the drug, chemical, and electronics sectors (Makri et al., 2010).

Media data were collected from the China Infobank, Wisers, and Baidu News databases. For each technology M&A, we conducted searches across the three databases using the acquirer's full name, abbreviation, stock code, as well as the target's full name and abbreviation. We excluded news that did not exclusively pertain to the sample technology M&As and those with fewer than 50 words. Missing media data could arise because each database contains only a subset of the total data, limited by financial resources and coverage capacity. To mitigate such data gaps, we manually collected news from each database. Additionally, we identified and removed duplicate media data found in different databases, often resulting from news replication and web crawling. For instance, a single news piece might have identical content but different headlines in two or more databases. These duplicates were systematically reviewed and eliminated. Appendix 3 presents a comprehensive list of media sources used in our study.

The number of technology M&As by year, presented in Panel C of Table 1, reveals an overall pattern of initial growth followed by a subsequent decline from 2009 to 2021. Technology M&As were infrequent during the early years (2009–2012) of our sample period. The number of technology M&As surged from a mere 30 in 2013 to a peak of 106 in 2015, marking the year with the highest concentration of technology M&As. This pattern aligns with trends observed in previous studies (Li et al., 2022; Wang et al., 2018).[20] Subsequently, the number of technology M&As steadily decreased, reaching just 18 in 2021. The rest columns of Panel C demonstrate that news coverage of our sample technology M&As exhibited similar temporal patterns over years.

(Insert Table 1 about here)

We obtain the patent count data from the Chinese State Intellectual Property Office and Baiteng. Data for other firm level variables are collected from the Chinese Stock Market &

[20] Wang et al. (2018) and Li et al. (2022) discuss the relation between 2014-2016 merger wave and financial policy (fiscal policy and monetary policy). According to Wang et al. (2018, page 22), "After the 2008 global financial crisis, the Chinese government announced a two-year 4 trillion Yuan stimulus package to boost the domestic economy because the export demand shrank dramatically in the global recession. Commercial banks were the main channels for the 4 trillion Yuan investment, and their credit ceilings were abolished to provide more credit to priority projects, the 'three rural issues: agriculture, rural areas and farmers,' middle and small-sized enterprises, technical innovation and industrial rationalization through mergers and acquisitions." According to Li et al. (2022, page 7), "A series of financial liberalization reforms were launched together with major policy efforts to mobilize resources from the financial system to achieve the state's various policy goals, such as the initiatives to 'mobilize the financial system to support small and micro-enterprises' and 'promote enterprise mergers, acquisitions, and restructuring,' as well as major policy campaigns in 2014–2015 under the slogan of 'Mass-innovation, Mass-entrepreneurship' which mobilized the entire state bureaucracy to generate policy innovations to stimulate entrepreneurship."

Accounting Research (CSMAR) database.

4.3. Summary Statistics

Appendix 5 details definitions and calculations for all variables utilized in our empirical analyses. Table 2 presents summary statistics for the variables employed in our study. Notably, for technology M&As, the means of the CARs is significantly positive, as indicated by a p-value of 0.00. On average, a technology M&A has a *MedSI* score of 2.60 (with a median of 2.06). This distribution is right-skewed, with the median falling below the mean. Notably, both means and medians of *MedSI* tend to be higher compared to sentiment of innovation measured based on analyst reports and M&A announcements. On average, the target firm has 1.64 granted invention patents and 2.06 granted utility patents around each M&A announcement.[21] In terms of control variables, we observe that 79% of technology M&As involve stock as a form of payment, 33% of stock shares are owned by the largest shareholder, and 15% of acquirers are state-owned enterprises. On average, acquirers have 8.26 directors on their boards. The correlation matrix is presented in Appendix 6, revealing no concern of multicollinearity in our regression analysis.

(Insert Table 2 about here)

5. Empirical Analyses

5.1. MedSI, Prediction, Bias, and Short-Term Post-Announcement Performance

Table 3 explores the relationship between *MedSI* and short-term post-announcement performance. In Columns (1) and (2), we observe that the coefficient of *MedSI* is significantly positive, suggesting a substantial impact of *MedSI* on short-term post-announcement

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[21] About 6.63% of our observations have neither invention patents nor utility patents in the targets. About 14.46% (11.65%) of the observations have only invention (utility) patents in the targets. About two third of the observations (67.27%) have both types of patents in the targets.

performance.[22] Specifically, in Column (2), *MedSI* exhibits a coefficient of 0.011, significant at the 5% level with a t-statistic of 2.28. This indicates that an increase in *MedSI* by one standard deviation (2.311) corresponds to an average abnormal return of 2.40% during the [−5, +5] window surrounding M&A announcements. *CARs* are positively associated with relative size and negatively associated with acquirer size and acquirer market-to-book ratio, consistent with the findings of Moeller et al. (2004). *CARs* are also negatively linked to acquirer stock return run-up, aligning with the results of Nguyen and Phan (2017) and Hossain and Javakhadze (2020). In sum, these results support the prediction of our first hypothesis, *H1*.

According to the regression results for Model (3) presented in Appendix 7, *MedSI* is positively associated with target's utility patents and Tobin's Q, while negatively related to acquirer's leverage ratio and target's size. The significantly positive coefficient for *UP* suggests that media coverage may focus on new applications of existing technologies rather than entirely novel technologies, indicating a potential superficial understanding of the target's innovation productivity.[23] The positive coefficient for *TobinQ_Tar* can be explained by higher Tobin's Q predicting greater innovation outcomes (Sevilir and Tian 2012), and consequently, a higher *MedSI*. Additionally, we observe that *MedSI* is significantly and negatively correlated with acquirer's leverage ratio and target's size. The fitted values of *MedSI* from this regression are referred to as the media sentiment prediction of innovation (*MedPred*), while the regression residuals are denoted as the media sentiment bias of innovation (*MedBias*).

In Column (3) of Table 3, we investigate the relationship between media sentiment prediction and bias of innovation and post-announcement performance. The significantly positive coefficient of *MedPred*, as reported in Column (3), indicates that media sentiment

[22] The regression results are similar by controlling M&A announcements sentiment of innovation (calculated based on the POT Section of M&A announcements) or M&A announcements sentiment of innovation (calculated based on the TCA Section of M&A announcements).

[23] Invention patents cover novel technologies and hence have higher innovative content than utility patents that cover new applications of existing technologies.

prediction of innovation, generated based on acquirer's and target's fundamentals, exerts a significant impact on short-term post-announcement performance. Similarly, the significantly positive coefficient of *MedBias* suggests that media's own opinions also play a vital role in short-term post-announcement performance. However, the magnitude of the coefficient for *MedPred* is approximately eleven times larger than that of *MedBias*. An increase in *MedPred* by one standard deviation is associated with a roughly five times larger increase in CARs compared to that resulting from *MedBias*. These findings collectively suggest that the return impact of media sentiment prediction of innovation (informed by acquirer's and target's fundamentals) significantly outweighs that of media sentiment bias of innovation (reflecting media's own opinions or bias). Most of the control variables also exhibit coefficients with the expected signs. These results align with the predictions of our hypotheses *H2* and *H3* regarding the impacts of media sentiment prediction and bias of innovation on short-term post-announcement performance in technology M&As.

(Insert Table 3 about here)

5.2. Do MedSI, Prediction, and Bias Affect Long-Term Post-Announcement Performance?

In Table 4, Columns (1) and (2) reveal that the coefficient of *MedSI* is not statistically significant, indicating that *MedSI* does not exert a significant impact on long-term post-announcement performance. In contrast, Columns (3) and (4) show that the coefficient of *MedPred* is significantly positive, whereas the coefficient of *MedBias* is statistically insignificant. This suggests that media sentiment prediction of innovation, derived from acquirer's and target's fundamentals, contains valuable information for long-term post-announcement performance, whereas media sentiment bias of innovation, representing media's own opinions or bias, does not have a significant effect. The difference in coefficients between *MedPred and MedBias* is both statistically and economically significant.

In summary, these results support the notion that both media sentiment prediction and bias of innovation have a short-term impact, but only media sentiment prediction of innovation exhibits a persistent impact on the long-term post-announcement performance. The reversal in market reaction to *MedSI* in the long term is likely attributed to bias. These findings confirm the predictions of our hypotheses *H2* and *H3* regarding the impacts of media sentiment prediction and bias of innovation on short-term post-announcement performance in technology M&As.

(Insert Table 4 about here)

However, our main variable of interest, *MedSI*, is unlikely to occur randomly. If *MedSI* and market reaction are jointly influenced by other unobservable firm characteristics, our regression results may be subject to omitted variable bias. Furthermore, the direction of causality could run from profitable M&As to *MedSI*, rather than vice versa. As we lack a natural experiment to address these endogeneity concerns, we employ an instrumental variables analysis to alleviate the endogeneity concerns on the causal interpretation of the associations identified in our baseline regression analysis.

We utilize the introduction of a high-speed rail connecting the cities of a firm's headquarters and a newspaper's headquarters as the instrumental variable, a method used in previous studies (e.g., You et al. 2018). We anticipate that the introduction of a high-speed rail between these cities will have a negative impact on the *MedSI* for two primary reasons. First, firms often engage in public relations activities, which can lead domestic media to refrain from covering negative news.[24] Consequently, a high-speed rail lowers the cost of journalists visiting firm locations, increases potential revenue from reporting, and facilitates more objective or critical reporting on target's innovation activities. Second, Chinese journalists frequently conduct telephone and written interviews, which may make them inclined to be

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[24] See "A-share IPO, paid silence and need urgent governance". In this report, Su Peike introduces a normality in China stock market that public relations of firms eliminate negative news and media become silent after paid by firms. https://www.reuters.com/article/column-su-peike-china-share-ipo-idCNKCS0I50U720141016.

overly optimistic or inaccurate in their reporting on acquirers due to their limited knowledge of firms.[25] As a result, the introduction of a high-speed rail reduces journalists' onsite visiting costs, reduces information asymmetry between the media and firms, and mitigates overly positive coverage of target's innovation activities. The introduction of a high-speed rail may also have a negative impact on the media sentiment prediction (bias) of innovation by reducing over-optimism. However, it is less likely to be associated with the post-announcement performance in M&As. Therefore, this instrumental variable meets both relevance and exclusion conditions.

We obtain information regarding the introduction year of high-speed rail connections from Chinese Research Data Services and construct the high-speed rail (*HSR*) instrument variable that equals one if there is a high-speed rail connection between the cities where the acquirer's and the newspaper's headquarters are located. We perform tests at the firm-news level and calculate the effective F-statistic, which exceeds the benchmark of 10, thereby passing the effective first-stage F-statistic test. The results based on *HSR* are reported in Table 5. Columns (1)–(3) present the first-stage linear regressions illustrating the relationship between *HSR* and *MedSI*, *MedPred*, and *MedBias*, respectively. The results in Columns (1)–(3) indicate that *HSR* is strongly negatively related to *MedSI*, *MedPred*, and *MedBias*, while controlling for a broad set of other regressors. Column (4) focuses on the acquirer's *CARs*. The coefficient of *MedSI*(*IV*) is positive and statistically significant (t = 2.18). Column (5) focuses on the acquirer's CARs. The coefficient of *MedPred*(*IV*) is positive and statistically significant (t = 2.11). Column (6) focuses on the acquirer's *CARs*. The coefficient of *MedBias*(*IV*) is positive and statistically significant (t = 2.06). Columns (7) and (8) focus on the BHARs. The coefficients for

[25] For example, Capital Week (governed by China Stock Exchange Executive Council and is one of most authoritative newspapers in China) used telephone interview and published a report titled " Ningbo Shanshan may acquire the 5% shares of a Latin American lithium mine" on June 13, 2010. This report had a broad impact in the markets. However, Ningbo Shanshan Co. LTD. (600884.SH) published a clarification announcement and denied the content of news on June 18, 2010. http://sem.bjtu.edu.cn/chinamerger/show-336-4313.html.

MedPred(*IV*) are positive and statistically significant (t = 1.81, t = 1.73). We control for industry and year-fixed effects and employ robust standard error estimation.

(Insert Table 5 about here)

6. Robustness Checks and Further Tests

6.1. Moderating Effect of Market-Level Investor Sentiment

Market reactions to positive news are generally more pronounced during high sentiment periods than during periods of low sentiment (Mian & Sankaraguruswamy, 2012). Investors, unable to distinguish biased news in the short run, may perceive both media sentiment prediction of innovation and media sentiment bias of innovation as positive news. Therefore, we anticipate that the market reaction to media sentiment prediction (bias) of innovation will be more significant when market-level investor sentiment is high. To measure market-level investor sentiment, we collect from CSMAR the China Standardized Investor Sentiment Index (*CSISI*), constructed based on Baker and Wurgler (2006). We match *CSISI* with the acquirer's media reporting window and classify acquirers below/above the median *CSISI* as Low/High *CSISI*.

In Panel A of Table 6, Columns (1) and (2) demonstrate that only the coefficient of *MedSI* in High *CSISI* is significantly positive. The magnitude of the coefficient of *MedSI* in High *CSISI* is approximately seven times larger than that in Low *CSISI*. An increase in *MedSI* of one standard deviation in High *CSISI* is associated with about seven times a larger increase in *CARs* than that in Low *CSISI*. These results suggest that investors with a more optimistic sentiment are more responsive to news descriptions of innovation, even if the news may be biased.

Columns (3) and (4) reveal that only the coefficients of *MedPred* and *MedBias* in High $CSISI$ are significantly positive. The magnitude of the coefficient of *MedPred* (*MedBias*) in High $CSISI$ is about seven (nine) times larger than that in Low *CSISI*. An increase in *MedPred*

(*MedBias*) of one standard deviation in High *CSISI* is associated with about six (nine) times a larger increase in *CARs* than that in Low *CSISI*. These results suggest that investors with a more optimistic sentiment are more responsive to both media sentiment prediction of innovation and media sentiment bias of innovation. Column (4) further shows that the magnitude of the coefficient of *MedPred* is about six times larger than that of *MedBias* and the difference in coefficients is statistically and economically significant (p-value is 0.01). These results are consistent with the previous finding that, in terms of magnitude, investors primarily respond to media sentiment prediction of innovation rather than media sentiment bias of innovation.

We also utilize the China Standardized Excluded Macro Factors Investor Sentiment Index (*CSEMFISI*) obtained from CSMAR and observe similar results in Panel B of Table 6.

(Insert Table 6 about here)

6.2. Moderating Effect of Investors Search Volume about Company's Innovation Activity

Previous studies have indicated that search engines facilitate the gathering and sharing of information relevant to investors, offering a platform for the instantaneous dissemination of news to a wide audience (Da et al., 2011). When investors search for a company's innovation activities, it is undeniable that they are more likely to be influenced quickly by news descriptions of innovation. Consequently, we propose that the market's response to media sentiment regarding innovation is stronger during periods of high search volume compared to periods of low search volume. Given that investors may struggle to discern biased news in the short run, we further suggest that the market's response to media sentiment predictions (biases) about innovation is more pronounced during high search volume than during low search volume. To gauge investors' search volume concerning a company's innovation activities, we employ Baidu Index's search volume as a proxy.[26] We use a set of keywords (Listed company + Innovation + Stock price) to obtain the search volume index (*SVI*), as these keywords reflect investor interest in understanding how a company's innovation activities may impact its stock price. Acquirers with *SVI* values below the median are classified as Low *SVI*, while those with *SVI* values above the median are classified as High *SVI*.

Before presenting the regression results for the moderating effect of investor search volume on innovation activity, we conduct a test and find that media sentiment regarding innovation exhibits no significant differences between Low *SVI* and High *SVI*, indicating that the media maintains a consistent reporting level of a target's innovation capabilities regardless of *SVI*.

Table 7 demonstrates that only the coefficients of *MedSI, MedPred* and *MedBias* in High *SVI* are significantly positive. The magnitude of their coefficients in High *SVI* is approximately three times greater than that in Low *SVI*. An increase in *MedSI, MedPred* and *MedBias* by one standard deviation in High *SVI* is associated with a roughly threefold larger increase in *CARs* compared to that in Low *SVI*. These results suggest that investors with greater interest in a company's innovation activities are more responsive to news descriptions of innovation, even when such news may be biased.[27]

(Insert Table 7 about here)

6.3. Robustness Checks

We perform a series of robustness checks to assess the robustness of our main results, as presented in Table 8. The multivariate regressions of short-term and long-term post-

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[26] "Considering that the Google search engine is not allowed in China, …Therefore, in this paper we choose the search data from Baidu as our main study object. Similar to Google trend, Baidu provides a service known as the Baidu Index, a weighted sum of the search volume for certain keywords that is calculated and published by the Baidu company. In addition, the Baidu Index offers three search volumes: search frequency from PC terminals, search frequency from mobile terminals, and the aggregate search frequency from the two types of terminals. Hence, the Baidu Index can both efficiently and roundly reflect the retail investor attention paid to stocks in China." (Wen et al. 2019, page 2)

[27] Although Column (4) shows that the magnitude of the coefficient on *MedPred* is about five times larger than that on $MedBias$. This difference in coefficients is statistically insignificant given the p-value of 0.19.

announcement performances are reported in Panel A and Panel B, respectively. Columns (1) and (2) of Panel A and Panel B present results for alternative measurements of media sentiment regarding innovation (*MedSIA*) calculated at the technology M&A level. First, we divide the number of keywords related to the target's innovation activities by the total number of words (in thousands) in a media report. Second, we obtain a value by multiplying the innovation keywords ratio of a report by 1 or −1 (if the sentiment of a report is greater than or equal to zero, the value is 1; otherwise, it is −1). Finally, we calculate the average of these values for all reports in a technology M&A. Columns (3) and (4) of Panel A and Panel B examine the subsample period from 2013 to 2021. Most of the technology M&As in our sample occurred between 2013 and 2019 (445 technology M&As). Subsamples allow us to exclude potentially extreme samples and obtain more robust results. Columns (5–10) of Panel A and Panel B report results for the subsamples of complete technology M&As, domestic technology M&As, and suspended technology M&As, respectively. Columns (11) and (12) of Panel A and Panel B report results when media sentiment regarding innovation is measured based on the eight largest nationwide business newspapers (You et al. 2018).[28] Overall, the results reported in Table 8 demonstrate the robustness of our findings.[29]

(Insert Table 8 about here)

6.4. Does *MedSI* Predict Target's Post-Announcement Innovation?

To assess whether media coverage accurately reflects a target's innovation productivity, we have developed the following regression model to investigate the relationship between media sentiment predictions/biases of innovation and a target's post-announcement innovation outcomes:

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[28] The eight largest nation-wide business newspapers in China identified in You et al. (2018) include: China Securities Journal, Securities Daily, Securities Times, Shanghai Securities Journal, China Business Journal, First Financial Daily, The Economic Observer, and 21st Century Business Herald.

[29] We also add technology M&As deals with no media reports in media reporting period to our sample and equal media sentiment of innovation to zero. The results are robust.

$$PostIP_i/PostUP_i = \beta_0 + \beta_1 MedSI_i + \beta_2 Controls_i + Year_i + Industry_i + \varepsilon_i \quad (6)$$

$$PostIP_i/PostUP_i = \beta_0 + \beta_1 MedPred_i + \beta_2 MedBias_i + \beta_3 Controls_i + Year_i + Industry_i + \varepsilon_i \quad (7)$$

In Models (6) and (7), the dependent variables are the target's pre-announcement granted invention patent counts (*PostIP*) and utility patent counts (*PostUP*). *PostIP* (*PostUP*) is calculated as the logarithm of one plus the target's number of granted invention (utility) patents in the post-announcement 1-year, 2-year, and 3-year windows, respectively. The primary independent variables of interest are *MedSI*, *MedPred*, and *MedBias*. Other independent variables include analyst sentiment of innovation, M&A announcement sentiment of innovation, the target's pre-announcement IP counts and UP counts, leverage ratio, size, Tobin's Q, ROA, deal payment, relative size, which have been previously documented in prior studies (Sevilir and Tian 2012).

In Panel A of Table 9, Columns (1)–(6) reveal that the coefficient of *MedSI* remains overall nonsignificant. This provides additional evidence that media sentiment regarding innovation may not significantly contribute to investors' ability to make informed investment decisions. Most of the control variables' coefficients align with the expected direction.

We further investigate the relationship between media sentiment predictions/biases of innovation and the target's post-announcement innovation outcomes. In Panel B of Table 9, Columns (1)–(6) demonstrate that the coefficient of *MedPred* is significant, while *MedBias* is not, suggesting that fundamentals, rather than the media's opinions, predict the target's invention innovation productivity. This finding provides additional support for the notion that media opinions offer limited value-relevant information, given that a target's innovation productivity is a crucial factor influencing its long-term performance. Most of the control variables' coefficients have the anticipated direction of effect.

(Insert Table 9 about here)

6.5. MedSI Measured Based on Different Types of Media

Previous studies have found that market-oriented media, under less political pressure, provides more information about firm fundamentals and conveys a more negative tone compared to media facing greater political pressure (You et al. 2018). Powerful local firms tend to receive more favorable overall coverage but may experience lower long-term performance due to corporate influence on the media (Borochin and Cu 2018). The internet has expanded and institutionalized as an alternative platform for news production and consumption. While it may not always be professional, it offers relatively novel content and formats (Mitchelstein & Boczkowski, 2009).

We include sentiment of innovation generated by market-oriented media (*MedSI_Mkt*), state-controlled media (*MedSI_Gov*), national-wide media (*MedSI_Nat*), local-wide media (*MedSI_Loc*), internet media (*MedSI_Int*), and press media (*MedSI_Pre*) as focal explanatory variables. According to summary statistics, the mean sentiment of innovation in market-oriented/local-wide/internet media is significantly smaller than that in state-controlled/national-wide/press *MedSI* (p-value is 0.00 for all three tests). We employ the same set of control variables utilized in Table 3 and present the results in Table 10. In Column (1), we observe that both *MedSI_Mkt* and *MedSI_Gov* coefficients are significantly positive, indicating that the market responds positively (negatively) to high (low) levels of both types of media sentiment about innovation. The economic magnitude of the $MedSI\_Mkt$ coefficient is less than that of *MedSI_Gov*, i.e., an increase in *MedSI_Mkt* (*MedSI_Gov*) by one standard deviation results in an average abnormal return of 0.93% (2.72%) during the [−5, +5] window. In Column (2), only the coefficient of *MedSI_Loc* is significantly positive, indicating that the market reacts positively (negatively) to high (low) local media sentiment about innovation. In Column (3), only the coefficient of *MedSI_Pre* is significantly positive, suggesting that the market responds positively (negatively) to high (low) press media sentiment about innovation.

(Insert Table 10 about here)

7. Conclusions

In this paper, we investigate whether media sentiment regarding targets' innovation enhances investors' ability to make informed investment decisions in technology M&As using media data in the Chinese market. We compute *MedSI* as a text-based metric representing the level of innovation productivity attributed to the target company in news reports and employ linear prediction to disect *MedSI* into *MedPred* and *MedBias*. Our empirical analysis reveals that *MedSI* predicts short-term post-announcement performance. While both *MedPred* and *MedBias* exert significantly positive short-term effects on the stock market performance of investment in technology M&As, only the former significantly impacts long-term post-announcement performance. Investors with more optimistic sentiment or a greater interest in a company's innovation activities tend to be more responsive to *MedSI*, *MedPred* and *MedBias*. The 2SLS IV regression results confirm the findings from the baseline regressions, and these results remain consistent across a battery of robustness checks. The discovery that only *MedPred* predicts a target's post-announcement innovation implies that fundamentals, rather than the media's subjective opinions, drive a target's innovation productivity.

Contributing to the literature on text analysis of innovation (Mukherjee et al. 2017; Bellstam et al. 2021, Chu et al. 2023), we introduce a valuable new measure of corporate innovation based on a textual analysis of media news releases, which play a pivotal role as information intermediaries in M&As. Unlike prior studies that primarily rely on R&D expenditure and patent counts to gauge product innovation in terms of investments and outcomes, our measure captures various facets of innovation, including collaboration and generalization. Research concerning the analysis of innovation descriptions in texts is still in its nascent stages. It is worth acknowledging that our text-based measure for *MedSI* may have certain limitations in terms of accuracy and objectivity. As artificial intelligence technology advances, newer text analysis methods with improved accuracy and objectivity may propel research utilizing text-based measures forward. Quantitatively assessing media bias in terms of a target's innovation potential in technology M&As has been challenging. Future research may benefit from our approach of distinguishing *MedSI* tied to fundamentals from media-biased sentiment and further exploring media sentiment bias in news related to other research inquiries.

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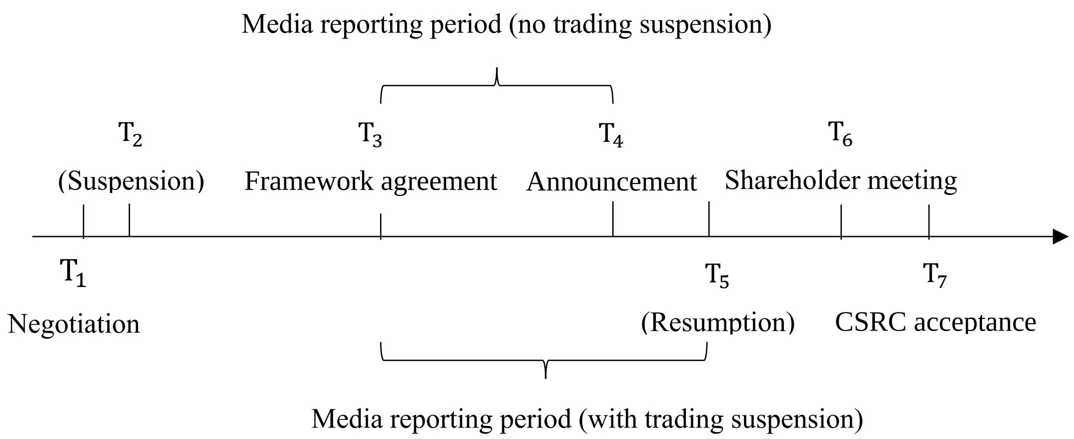
Figure 1: Timeline of A Technology M&A and Media Reporting Period

This figure depicts the general process of a technology M&A. After the acquirer negotiates with the target (T_1), it is likely to apply to the stock exchange for a trading suspension (T_2). In our sample, 96.3% of the technology M&As involved a suspension. Next, the acquirer announces the framework agreement (T_3), which is defined as the acquirer disclosure day. During the period T_1 to T_3, media have no access to technology M&A information because of deal confidentiality. Then, the acquirer publishes the technology M&A announcements containing the transaction details on date T_4, which is the announcement date for a technology M&A with no trading suspension. If a trading suspension was granted on date T_2, the acquirer resumes trading on date T_5, which is the announcement date for technology M&As with a trading suspension. The acquirer convenes a shareholder meeting (T_6) to discuss technology M&A issues. After the shareholder meeting approves the technology M&A plan, the CSRC accepts or rejects the merger application submitted by the acquirer (T_7). If the acquirer is not subject to a trading suspension, we define the period from T_3 to T_4 as the media reporting period. If the acquirer is subject to a trading suspension, we define the period from T_3 to T_5 as the media reporting period.[30]



[30] The media reporting period lasts on average 105.47 days with a minimum of one day and a maximum of 788 days. The standard deviation amongst the total number of 498 observations is 75.15 according to the statistics of our final sample.

Table 1: Sample Selection

Panel A reports the sample selection on technology M&As of all A-share listed companies in the WIND database announced between June 2008 and December 2021. Panel B illustrate the industry distribution of final sample. Panel C presents yearly distributions of technology M&As, news items, and media sources. We classify news items according to the year of the technology M&As which the item belongs to. "News num." is the number of media reports, including publications and websites, for a given period. "News per tech-M&A" is the number of media reports divided by the number of technology M&As for a given period. "Media sources num." is the number of media sources, including publications and websites, for a given period. "News per media source" is the number of media reports divided by the number of media sources for a given period.

Panel A: Matching process	Observations
All announced MAR deals	2,052
Excluding back-door listing deals [31], holistic listing deals [32], or privatization deals	326
Excluding deals with multiple targets[33]	487
Excluding the acquirer with a special treatment (ST) designation[34]	61
Excluding deals with incomplete status	57
Excluding deals with missing payment and merger size	53
Excluding deals without M&A announcements	56
Excluding deals that do not meet the definition of technology M&As	503
Excluding deals with no media reports in media reporting period	11
Final sample of technology M&As	498

Panel B: Industry Distribution of Final Sample	Freq.	Percent	Cum.
Transportation, Warehousing, and Postal Services	5	1.00	1.00
Accommodation and Food Services	1	0.20	1.20
Information Transmission, Software, and Information Technology Services	37	7.43	8.63
Agriculture, Forestry, Animal Husbandry, and Fisheries	6	1.20	9.84
Manufacturing	394	79.12	88.96
Construction	4	0.80	89.76
Real Estate	10	2.01	91.77
Wholesale and Retail Trade	16	3.21	94.98
Culture, Sports, and Entertainment	1	0.20	95.18
Water Conservation, Environmental Protection, and Public Facility	3	0.60	95.78

31 Back-door listing deals are also called as reverse merger. Liu et al. (2019, page 49) introduce reverse merger as follows: "In China, however, the stock of a small, listed firm is typically priced to reflect a substantial component of value related not to the firm's underlying business but instead to the Chinese initial public offering (IPO) process. In China, the IPO market is strictly regulated, and a growing demand for public listing confronts the low processing capacity of the regulatory bureau to approve IPOs. As a consequence, private firms seek an alternative approach, a reverse merger, to become public in a timely manner. In a reverse merger, a private firm targets a publicly traded company, a so-called shell, and gains control rights by acquiring its shares. The shell then buys the private firm's assets in exchange for newly issued shares. While reverse mergers occur elsewhere, IPO constraints are sufficiently tight in China such that the smallest firms on the major exchanges become attractive shell targets, unlike in the US, for example." Back-door listing deals are not similar to M&As transactions in the developed market. Therefore, we exclude back-door listing deals.

32 Holistic listing deals are referred to the listing that controlling shareholder injects group assets into a listed company through merger and realizes the whole group to come into the market (Huang et al., 2010). Holistic listing deals are not similar to M&As transactions in the developed market. Therefore, we exclude holistic listing deals.

33 Alperovych et al. (2021) examine completed or abandoned M&A transactions involving unlisted targets to determine the effect of transaction rumors from media on deal-closing propensity and transaction values. In their study, multi-target deals are excluded.

34 In China, the special treatment (ST) designation is a delisting warning for firms typically in financial distress. Stocks denoted ST are subject to different trading rules Tao et al. (2019). Therefore, we exclude deals whose acquirers are with a ST designation.

Management			
Electricity, Heat, Gas, and Water Production and Supply	1	0.20	95.98
Scientific Research and Technology Services	10	2.01	97.99
Miscellaneous	1	0.20	98.19
Mining	9	1.81	100.00
Total	498	100.00	

Panel C: Yearly Distribution

	Tech-M&As	News	News per Tech-M&A	Media sources	News per media source
2009	1	1	1	1	1
2010	2	8	4	4	2
2011	1	9	9	6	1.5
2012	7	39	5.57	20	1.95
2013	30	139	4.42	23	6.04
2014	63	317	5.03	35	9.06
2015	106	477	4.50	58	8.22
2016	97	522	5.38	69	7.57
2017	81	372	4.59	53	7.02
2018	50	244	4.88	54	4.52
2019	18	71	3.94	28	2.54
2020	24	110	4.58	30	3.67
2021	18	98	5.44	32	3.06

Table 2: Summary Statistics

All variables are as defined in Appendix 5.

Variable	Sample	Mean	SD	Min.	Median	Max.
Panel A: Dependent Variables						
CAR	498	0.09	0.280	-0.59	0.06	0.67
$VBHAR_{12}$	498	-0.11	0.678	-2.12	-0.16	2.72
$EBHAR_{12}$	498	0.09	0.634	-1.03	-0.02	3.08
$PostIP_1$	498	0.65	0.991	0.00	0.00	4.37
$PostIP_2$	480	0.89	1.153	0.00	0.69	5.10
$PostIP_3$	456	1.03	1.228	0.00	0.69	5.55
$PostUP_1$	498	0.95	1.132	0.00	0.00	4.01
$PostUP_2$	480	1.38	1.365	0.00	1.24	4.68
$PostUP_3$	456	1.68	1.505	0.00	1.79	5.27
Panel B: Independent Variables						
$MedSI$	498	2.60	2.311	0.00	2.06	11.31
$AnaSI$	498	0.77	1.612	0.00	0.00	7.18
$AnnSI$	498	0.12	0.078	0.00	0.11	0.34
IP	498	1.64	1.356	0.00	1.39	6.76
UP	498	2.06	1.555	0.00	2.30	5.25
$Size\_Acq$	498	22.29	0.764	20.69	22.30	24.47
ROA_Acq	498	0.05	0.070	-0.35	0.05	0.20
MB_Acq	498	5.61	3.855	0.92	4.51	21.21
Liq_Acq	498	0.19	0.140	0.01	0.15	0.63
Lev_Acq	498	0.35	0.195	0.03	0.31	0.82
$Top1\_Acq$	498	0.33	0.134	0.11	0.32	0.66
Age_Acq	498	1.82	0.820	0.00	1.79	3.26
$BrdSize\_Acq$	498	2.21	0.164	1.79	2.30	2.56
$IndSize\_Acq$	498	0.38	0.049	0.33	0.36	0.50
$Equity$	498	0.79	0.411	0.00	1.00	1.00
$RelVal$	498	0.30	0.293	0.01	0.21	1.76
$RunUp\_Acq$	498	1.37	0.931	0.52	1.14	6.38
SOE_Acq	498	0.15	0.358	0.00	0.00	1.00
Lev_Tar	498	0.51	0.248	0.04	0.52	1.46
$Size\_Tar$	498	11.60	1.008	9.36	11.48	14.51
$TobinQ\_Tar$	498	0.64	1.037	-2.03	0.60	3.47
ROA_Tar	498	0.10	0.140	-0.37	0.08	0.70

Table 3: Effect of MedSI on Short-Term Post-Announcement Performance

This table reports results for the multivariate regression of short-term post-announcement performance on *MedSI* and control variables. All variables are as defined in Appendix 5. The *t*-statistics shown in parentheses are based on standard errors adjusted for heteroscedasticity. Significance at the 1%, 5%, or 10% level is indicated by ***, **, or *, respectively.

DV = CARs	(1)	(2)	(3)
$MedSI$	0.012**	0.011**	
	(2.48)	(2.28)	
$MedPred$			0.095***
			(3.09)
$MedBias$			0.009*
			(1.88)
$AnaSI$		0.008	0.006
		(1.12)	(0.80)
$AnnSI$		-0.059	-0.098
		(-0.39)	(-0.65)
IP	0.013	0.013	0.015*
	(1.59)	(1.54)	(1.77)
UP	-0.006	-0.005	-0.026**
	(-0.92)	(-0.77)	(-2.49)
$Size\_Acq$	-0.033*	-0.035*	-0.039**
	(-1.70)	(-1.79)	(-2.06)
ROA_Acq	0.119	0.111	0.035
	(0.71)	(0.66)	(0.20)
MB_Acq	-0.011**	-0.011**	-0.012***
	(-2.49)	(-2.52)	(-2.85)
Liq_Acq	0.145	0.140	0.042
	(1.49)	(1.44)	(0.41)
Lev_Acq	0.065	0.061	0.212**
	(0.79)	(0.74)	(2.17)
$Top1\_Acq$	-0.058	-0.056	-0.041
	(-0.65)	(-0.62)	(-0.46)
Age_Acq	-0.017	-0.017	-0.013
	(-0.85)	(-0.84)	(-0.64)
$BrdSize\_Acq$	-0.086	-0.085	-0.073
	(-0.98)	(-0.96)	(-0.83)
$IndSize\_Acq$	-0.345	-0.348	-0.336
	(-1.18)	(-1.19)	(-1.14)
$Equity$	0.017	0.018	0.008
	(0.65)	(0.71)	(0.32)
$RelVal$	0.185***	0.184***	0.225***
	(4.57)	(4.53)	(5.28)
$RunUp\_Acq$	-0.110***	-0.108***	-0.110***
	(-8.98)	(-8.79)	(-8.94)
SOE_Acq	-0.024	-0.023	-0.014
	(-0.70)	(-0.67)	(-0.40)
$Cons$	1.257***	1.311***	0.971**
	(2.91)	(3.01)	(2.22)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	498	498	498
Adjusted R^2	0.38	0.38	0.39
$MedPred$ - $MedBias$			0.094***

Test of difference [p-value]	0.00

Table 4: Media Sentiment of Innovation on Long-term Post-Announcement Performance

This table reports results for the multivariate regression of post-announcement performance on media sentiment of innovation and control variables. All variables are as defined in Appendix 5. The sample period is from 2009 to 2021. The t-statistics shown in parentheses are based on standard errors adjusted for heteroscedasticity. Significance at the 1%, 5%, or 10% level is indicated by ***, **, or *, respectively.

	(1)	(2)	(3)	(4)
DVs	$VBHARs_{12}$	$EBHARs_{12}$	$VBHARs_{12}$	$EBHARs_{12}$
$MedSI$	0.005	0.007		
	(0.32)	(0.49)		
$MedPred$			0.242**	0.171*
			(2.19)	(1.73)
$MedBias$			-0.000	0.004
			(-0.01)	(0.24)
$AnnSI$	0.031	0.028	0.026	0.025
	(1.41)	(1.29)	(1.11)	(1.07)
$AnaSI$	-0.835*	-0.772*	-0.948*	-0.850**
	(-1.67)	(-1.79)	(-1.93)	(-1.97)
IP	0.055**	0.058**	0.061**	0.062**
	(2.14)	(2.32)	(2.35)	(2.49)
UP	-0.013	-0.020	-0.070*	-0.060*
	(-0.60)	(-0.98)	(-1.82)	(-1.69)
$Size\_Acq$	-0.045	-0.100*	-0.060	-0.111**
	(-0.76)	(-1.96)	(-1.08)	(-2.24)
ROA_Acq	-0.343	-0.290	-0.598	-0.467
	(-0.71)	(-0.63)	(-1.26)	(-1.04)
MB_Acq	-0.008	-0.010	-0.010	-0.011
	(-0.62)	(-0.87)	(-0.83)	(-1.03)
Liq_Acq	-0.016	0.005	-0.342	-0.220
	(-0.04)	(0.01)	(-0.89)	(-0.62)
Lev_Acq	-0.217	-0.080	0.214	0.219
	(-0.77)	(-0.32)	(0.63)	(0.68)
$Top1\_Acq$	0.032	0.036	0.053	0.051
	(0.12)	(0.14)	(0.19)	(0.20)
Age_Acq	0.007	0.002	0.013	0.007
	(0.11)	(0.04)	(0.23)	(0.13)
$BrdSize\_Acq$	-0.114	-0.081	-0.111	-0.078
	(-0.41)	(-0.30)	(-0.40)	(-0.29)
$IndSize\_Acq$	-0.669	-0.805	-0.668	-0.804
	(-0.72)	(-0.90)	(-0.73)	(-0.90)
$Equity$	0.016	0.037	-0.011	0.018
	(0.21)	(0.53)	(-0.13)	(0.25)
$RelVal$	0.130	0.165	0.237	0.239
	(0.74)	(0.96)	(1.24)	(1.27)
$RunUp\_Acq$	-0.064*	-0.082***	-0.072**	-0.087***
	(-1.94)	(-2.80)	(-2.16)	(-2.95)
SOE_Acq	-0.052	-0.093	-0.016	-0.068
	(-0.59)	(-1.25)	(-0.17)	(-0.89)
Cons	1.267	2.466*	0.499	1.934
	(0.87)	(1.81)	(0.32)	(1.35)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	387	387	387	387

Adjusted R^2	0.15	0.19	0.16	0.19

Table 5: Instrumental Variables Analysis of Effect of Media Sentiment of Innovation on Short-Term Post-Announcement Performance

This table reports instrumental variables (IV) estimates of the multivariate regression of short-term post-announcement performance on media sentiment of innovation and control variables at firm-news level. The IV is high-speed rail (HSR) that equals one if there is a high-speed rail connection between the cities of the headquarters of the acquirer and the newspaper, zero otherwise. Columns (1-3) report the first-stage linear regressions showing the relation between the IV and $MedSI, MedPred,$ and $MedBias$, respectively. Columns (4-6) report the second-stage IV linear regressions of $MedSI(IV)$, $MedPred(IV)$, and $MedBias(IV)$ on $CARs$. Columns (7) and (8) report the second-stage IV linear regression of $MedPred(IV)$ on $VBHARs_{12}$ and $EBHARs_{12}$, respectively. All variables are as defined in Appendix 5. The *t*-statistics shown in parentheses are based on standard errors adjusted for heteroscedasticity. Significance at the 1%, 5%, or 10% level is indicated by ***, **, or *, respectively.

DVs	(1) $MedSI$	(2) $MedPred$	(3) $MedBias$	(4) $CARs$	(5) $CARs$	(6) $CARs$	(7) $VBHARs_{12}$	(8) $EBHARs_{12}$
HSR	-0.462**	-0.041**	-0.441**					
	(-2.40)	(-1.98)	(-2.29)					
$MedSI(IV)$				0.108**				
				(2.18)				
$MedPred(IV)$					1.217**		3.149*	2.659*
					(2.11)		(1.81)	(1.73)
$MedPred$			-0.449**			0.146***		
			(-2.32)			(4.59)		
$MedBias(IV)$						0.104**		
						(2.06)		
$MedBias$		-0.005**			0.007*		0.019*	0.016
		(-2.32)			(1.82)		(1.69)	(1.62)
$AnaSI$	0.249***	0.033***	0.231***	-0.010	-0.024	-0.010	-0.094*	-0.080
	(5.84)	(7.34)	(5.37)	(-0.70)	(-1.23)	(-0.77)	(-1.67)	(-1.62)
$AnnSI$	6.294***	0.844***	5.844***	-0.660**	-1.015**	-0.673**	-2.723*	-2.275*
	(6.64)	(8.33)	(6.09)	(-2.12)	(-2.06)	(-2.28)	(-1.85)	(-1.76)
IP	0.056	0.090***	0.006	0.004	-0.100*	0.000	-0.224	-0.178
	(1.04)	(15.74)	(0.11)	(0.53)	(-1.91)	(0.00)	(-1.43)	(-1.29)
UP	0.150***	0.171***	0.056	-0.016*	-0.207**	-0.022***	-0.526*	-0.447*
	(3.30)	(35.32)	(1.00)	(-1.71)	(-2.12)	(-3.11)	(-1.80)	(-1.73)
$Size\_Acq$	0.088	-0.001	0.089	-0.063***	-0.052***	-0.063***	-0.032	-0.046
	(0.77)	(-0.10)	(0.78)	(-4.84)	(-3.45)	(-4.91)	(-0.75)	(-1.25)
ROA_Acq	-2.010	-1.940***	-0.941	0.746***	2.891**	0.820***	6.908**	6.005**

	(-1.57)	(-14.26)	(-0.71)	(4.06)	(2.57)	(4.99)	(2.04)	(2.01)
MB_Acq	-0.032	-0.017***	-0.023	-0.003	0.014	-0.003	0.050	0.044
	(-1.49)	(-7.50)	(-1.04)	(-1.17)	(1.34)	(-1.03)	(1.58)	(1.57)
Liq_Acq	-0.123	0.034	-0.142	0.290***	0.236***	0.288***	0.295	0.233
	(-0.19)	(0.50)	(-0.23)	(3.63)	(2.63)	(3.69)	(1.23)	(1.12)
Lev_Acq	-0.852*	-0.945***	-0.331	0.164**	1.222**	0.201***	2.936*	2.450*
	(-1.86)	(-19.42)	(-0.67)	(2.31)	(2.20)	(3.28)	(1.78)	(1.68)
$Top1\_Acq$	0.000	-0.117*	0.065	-0.109	0.033	-0.104	0.089	0.063
	(0.00)	(-1.96)	(0.12)	(-1.52)	(0.36)	(-1.48)	(0.32)	(0.26)
Age_Acq	-0.182	-0.073***	-0.142	-0.006	0.063	-0.004	0.168	0.119
	(-1.53)	(-5.79)	(-1.19)	(-0.39)	(1.45)	(-0.26)	(1.27)	(1.02)
$BrdSize\_Acq$	-0.316	-0.093	-0.265	-0.087	-0.008	-0.084	0.398	0.344
	(-0.53)	(-1.47)	(-0.45)	(-1.34)	(-0.09)	(-1.33)	(1.48)	(1.45)
$IndSize\_Acq$	-2.252	-0.022	-2.246	-0.262	-0.475**	-0.269	-0.427	-0.390
	(-1.21)	(-0.11)	(-1.21)	(-1.10)	(-2.02)	(-1.15)	(-0.69)	(-0.71)
$Equity$	0.273	0.077***	0.231	0.014	-0.051	0.012	-0.348**	-0.287**
	(1.52)	(4.04)	(1.28)	(0.54)	(-0.97)	(0.48)	(-2.23)	(-2.11)
$RelVal$	-0.144	-0.327***	0.036	0.216***	0.598***	0.229***	1.251**	1.077**
	(-0.55)	(-11.69)	(0.13)	(6.58)	(3.12)	(7.01)	(2.15)	(2.10)
$RunUp\_Acq$	0.081	0.024**	0.068	-0.124***	-0.144***	-0.124***	-0.158***	-0.149***
	(0.90)	(2.47)	(0.76)	(-10.04)	(-6.60)	(-10.36)	(-2.72)	(-2.91)
SOE_Acq	-0.082	-0.076***	-0.040	-0.014	0.070	-0.011	0.107	0.067
	(-0.38)	(-3.35)	(-0.19)	(-0.53)	(1.28)	(-0.45)	(0.67)	(0.48)
Cons	3.872	7.087***	2.357	1.768***	-0.173	1.700***	-4.959	-3.571
	(1.12)	(19.19)	(0.63)	(5.50)	(-0.17)	(5.35)	(-1.64)	(-1.34)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2407	2407	2407	2407	2407	2407	2407	2407

Table 6: The Moderating Effect of Investors Sentiment

This table reports results for the multivariate regression of short-term post-announcement performance on media sentiment prediction / bias of innovation and control variables. We use CSISI and CSEMFISI downloaded from CSMAR in Panel A and Panel B, respectively. We match $CSISI$ and $CSEMFISI$ in acquirer's media reporting window. Acquirers below the median of $CSISI$ or $CSEMFISI$ are classified as Low and acquirers above the median of $CSISI$ or $CSEMFISI$ are classified as High. All other variables are defined in Appendix 5. The sample period is from 2009 to 2021. The t-statistics shown in parentheses are based on standard errors adjusted for heteroscedasticity. Significance at the 1%, 5%, or 10% level is indicated by ***, **, or *, respectively.

Panel A:				
DV: $CARs$	(1)	(2)	(3)	(4)
	$Low\ CSISI$	$High\ CSISI$	$Low\ CSISI$	$High\ CSISI$
$MedSI$	0.003	0.022***		
	(0.39)	(2.68)		
$MedPred$			0.016	0.112***
			(0.22)	(3.20)
$MedBias$			0.002	0.018**
			(0.37)	(2.26)
Other Controls	Yes	Yes	Yes	Yes
Cons	1.795***	0.276	1.781***	-0.625
	(3.14)	(0.35)	(3.06)	(-0.77)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	250	248	250	248
Adjusted R^2	0.43	0.41	0.43	0.43
Difference of $MedSI/MedPred/MedBias$	-0.019*		-0.096*/-0.016*	
Test of difference [p-value]	0.056		0.081/0.065	

Panel B:				
DV: $CARs$	(1)	(2)	(3)	(4)
	$Low\ CSEMFISI$	$High\ CSEMFISI$	$Low\ CSEMFISI$	$High\ CSEMFISI$
$MedSI$	0.000	0.024***		
	(0.05)	(2.89)		
$MedPred$			0.047	0.115***
			(0.70)	(3.17)
$MedBias$			-0.000	0.020**
			(-0.06)	(2.47)
Other Controls	Yes	Yes	Yes	Yes
Cons	1.962***	0.400	1.853***	-0.416
	(3.45)	(0.49)	(3.13)	(-0.49)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	249	249	249	249
Adjusted R^2	0.43	0.41	0.43	0.43
Difference	-0.024***		-0.068 /-0.020*	
Test of difference [p-value]	0.01		0.124/0.023	

Table 7: The Moderating Effect of Investors Search Volume

This table reports results for the multivariate regression of short-term post-announcement performance on media sentiment prediction / bias of innovation and control variables. We calculate investors' search volume using Baidu index.[35] We search the keywords "Listed company + Innovation + Stock price" in acquirer's media reporting window and get the search volume of the keywords (SVI). SVI reflects the investors' interest on whether and how company's innovation activity will affect stock price. Acquirers below the median of SVI are classified as Low and acquirers above the median of SVI are classified as High. All variables are as defined in Appendix 5. The sample period is from 2009 to 2021. The *t*-statistics shown in parentheses are based on standard errors adjusted for heteroscedasticity. Significance at the 1%, 5%, or 10% level is indicated by ***, **, or *, respectively.

DV:$CARs$	(1)	(2)	(3)	(4)
	$Low\ SVI$	$High\ SVI$	$Low\ SVI$	$High\ SVI$
$MedSI$	0.008	0.021***		
	(1.23)	(2.78)		
$MedPred$			0.033	0.098*
			(1.10)	(1.67)
$MedBias$			0.007	0.020**
			(1.08)	(2.57)
Other Controls	Yes	Yes	Yes	Yes
Cons	1.440**	1.078	1.382**	0.817
	(2.53)	(1.63)	(2.41)	(1.20)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	248	247	248	247
Adjusted R^2	0.43	0.28	0.43	0.28
Difference of $MedSI/MedPred/MedBias$	-0.013*		-0.065*/-0.013*	
Test of difference [p-value]	0.087		0.086/0.083	

[35] "Similar to Google trend, Baidu provides a service known as the Baidu Index, a weighted sum of the search volume for certain keywords that is calculated and published by the Baidu company. In addition, the Baidu Index offers three search volumes: search frequency from PC terminals, search frequency from mobile terminals, and the aggregate search frequency from the two types of terminals. Hence, the Baidu Index can both efficiently and roundly reflect the retail investor attention paid to stocks in China." (Wen et al., 2019)

Table 8: Robustness Checks

This table reports results for the robustness check.
Panel A reports results for the multivariate regression of short-term post-announcement performance and Panel B reports results for the multivariate regression of long-term post-announcement performance. Columns (1) and (2) of Panel A and B report results of alternative measurement of media sentiment of innovation. Alternative measurement of media sentiment of innovation is calculated at technology M&As level. First, we divide the number of innovation keywords which is only related to target's innovation activity by the total number of words (in thousands) in a media report. Second, we get the value which is the innovation keywords ratio of a report multiplied by 1 or -1 (if of the sentiment of a report is greater than or equal to zero, value 1, otherwise, value -1). We take the average of the values of all reports in a technology M&A. Finally, we take the average of the values of all reports in a technology M&A. Columns (3) and (4) of Panel A and Panel B examine subsample period of 2013-2021. Columns (5) and (6) of Panel A and Panel B report results of subsample of complete technology M&As. Columns (7) and (8) of Panel A and Panel B report results of subsample of domestic technology M&As. Columns (9) and (10) of Panel A and Panel B report results of subsample of suspended technology M&As. Columns (11) and (12) of Panel A and Panel B report results of subsample of eight largest nation-wide business newspapers (You et al. 2018). All variables are as defined in Appendix 5. The *t*-statistics shown in parentheses are based on standard errors adjusted for heteroscedasticity. Significance at the 1%, 5%, or 10% level is indicated by ***, **, or *, respectively.

Panel A:

DV: $CARs$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Alternative Measurement		2013-2021		Complete Tech-M&As		Domestic Tech-M&As		Suspended Tech-M&As		Eight Largest Business Newspapers	
$MedSI$	0.010**		0.011**		0.013**		0.011**		0.012**		0.033***	
	(2.17)		(2.31)		(2.35)		(2.06)		(2.28)		(2.70)	
$MedSIPred$		0.079***		0.097***		0.088**		0.099***		0.112***		0.237***
		(3.04)		(3.15)		(2.55)		(3.11)		(3.11)		(3.09)
$MedSIBias$		0.008*		0.009*		0.011**		0.009*		0.010*		0.029**
		(1.74)		(1.91)		(2.01)		(1.69)		(1.95)		(2.36)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cons	1.299***	0.967**	1.240***	0.989**	1.444***	1.079**	1.132**	0.722	1.446***	1.092**	1.373***	1.534***
	(2.97)	(2.21)	(2.69)	(2.19)	(2.94)	(2.20)	(2.34)	(1.46)	(3.07)	(2.34)	(3.11)	(3.50)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	498	498	487	487	387	387	465	465	466	466	498	498
Adjusted R^2	0.38	0.39	0.38	0.39	0.38	0.39	0.38	0.40	0.38	0.39	0.38	0.39

Panel B:

DV:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$VBHARs_{12}$	Alternative Measurement		2013-2021		Complete Tech-M&As		Domestic Tech-M&As		Suspended Tech-M&As		Eight Largest Business Newspapers	
MedSI	0.004		0.005		0.005		0.004		0.008		0.004	
	(0.29)		(0.33)		(0.32)		(0.27)		(0.53)		(0.12)	
MedSIPred		0.136*		0.165*		0.203**		0.174**		0.215**		0.358
		(1.86)		(1.96)		(2.10)		(1.99)		(2.20)		(1.62)
MedSIBias		0.000		0.001		0.000		0.000		0.004		-0.003
		(0.00)		(0.07)		(0.00)		(0.03)		(0.27)		(-0.11)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cons	0.551	-0.083	0.016	-0.453	1.267	0.313	-0.413	-1.201	-0.050	-0.781	0.562	0.841
	(0.44)	(-0.06)	(0.01)	(-0.33)	(0.87)	(0.20)	(-0.31)	(-0.83)	(-0.04)	(-0.64)	(0.44)	(0.68)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	498	498	487	487	387	387	465	465	466	466	498	498
Adjusted R^2	0.38	0.39	0.38	0.39	0.38	0.39	0.38	0.40	0.38	0.39	0.38	0.39

Table 9: Media Sentiment of Innovation on Target's Post-Announcement Innovation Outcomes

Panel A of this table reports the results of the multivariate regression of target's post-announcement innovation outcomes on media sentiment of innovation and control variables. Panel B of this table reports the results of the multivariate regression of target's post-announcement innovation outcomes on media sentiment bias of innovation and control variables. The dependent variables are target's number of granted invention patents ($PostIP$) or utility patents ($PostUP$) in post-announcement 1-year, 2-year and 3-year window. All variables are as defined in Appendix 5. The sample period is from 2009 to 2021. The t-statistics shown in parentheses are based on standard errors adjusted for heteroscedasticity. Significance at the 1%, 5%, or 10% level is indicated by ***, **, or *, respectively.

Panel A:

	(1)	(2)	(3)	(4)	(5)	(6)
DVs	$PostIP_1$	$PostIP_2$	$PostIP_3$	$PostUP_1$	$PostUP_2$	$PostUP_3$
$MedSI$	0.030*	0.028	0.025	0.020	0.004	0.002
	(1.81)	(1.37)	(1.09)	(0.98)	(0.16)	(0.08)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Cons	-0.979	-1.191	-0.568	-1.068	-0.792	1.526
	(-1.54)	(-1.51)	(-0.64)	(-1.42)	(-0.98)	(1.59)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	498	480	456	498	480	456
Adjusted R^2	0.38	0.40	0.39	0.38	0.42	0.40

Panel B:

	(1)	(2)	(3)	(4)	(5)	(6)
DVs	$PostIP_1$	$PostIP_2$	$PostIP_3$	$PostUP_1$	$PostUP_2$	$PostUP_3$
$MedPred$	0.269***	0.261**	0.215*	0.027	-0.023	0.106
	(3.17)	(2.55)	(1.90)	(0.26)	(-0.19)	(0.73)
$MedBias$	0.021	0.019	0.017	0.019	0.005	-0.002
	(1.24)	(0.94)	(0.75)	(0.95)	(0.20)	(-0.09)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Cons	-2.351***	-2.526***	-1.667	-1.110	-0.638	0.925
	(-2.96)	(-2.63)	(-1.54)	(-1.22)	(-0.61)	(0.76)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	498	480	456	498	480	456
Adjusted R^2	0.39	0.41	0.39	0.38	0.42	0.40

Table 10: Different Types of Media Sentiment of Innovation and Short-Term Post-Announcement Performance

This table reports results for the multivariate regression of short-term post-announcement performance on media sentiment of innovation and control variables. The state-controlled media is either owned or controlled by the government and nonprofit organizations. The market-oriented media is either owned or controlled by financial institutions, public companies, or wealthy individuals. The national-wide media is national release. The local-wide media is province or prefecture-level city release. The press media is press firm. The Internet media is Internet firm. We calculate state-controlled media sentiment of innovation ($MedSI\_Gov$) only use state-controlled media reports. We first calculate the innovation keywords ratio of a market-oriented media report by dividing the number of innovation keywords only related to target's innovation productivity by the total number of words (in thousands) in a market-oriented media report. The innovation keywords ratio of a market-oriented media report is then multiplied by the sentiment of a market-oriented media report. Finally, we take the average of the values of all market-oriented media reports in a technology M&A. So are the others. All variables are as defined in Appendix 5. The sample period is from 2009 to 2021. The t-statistics shown in parentheses are based on standard errors adjusted for heteroscedasticity. Significance at the 1%, 5%, or 10% level is indicated by ***, **, or *, respectively.

DV: *CARs*	(1)	(2)	(3)
$MedSI\_Mkt$	0.010*		
	(1.68)		
$MedSI\_Gov$	0.008*		
	(1.89)		
$MedSI\_Nat$		0.008*	
		(1.72)	
$MedSI\_Loc$		0.022**	
		(2.27)	
$MedSI\_Int$			-0.013
			(-1.47)
$MedSI\_Pre$			0.013**
			(2.58)
Other Controls	Yes	Yes	Yes
Cons	1.373***	1.297***	1.261***
	(3.14)	(2.96)	(2.89)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	498	498	498
Adjusted R^2	0.38	0.39	0.38
Difference	0.002	-0.014	-0.026**
Test of difference [p-value]	0.74	0.19	0.01

Appendix 1: Qian Shan Yao Ji's Acquisition of Hong Hao Ji Yin

In 2014, the acquirer, Qian Shan Yao Ji in the medical equipment industry, acquired the target, Hong Hao Ji Yin, in the biopharmaceutical industry. According to *National Business Daily*, one of the mainstream business newspapers covering the M&A, "Hong Hao Ji Yin is a high-tech company focusing on gene chip technology, which is committed to developing a series of gene diagnostic kits for guiding individual drug therapy. The founder of Hong Hao Ji Yin, Honghao Zhou, is a Member of the Chinese Academy of Engineering and proposes the theory of personalized medicine … At present, Hong Hao Ji Yin has two core technologies of 'pharmacogenomics application technology' and 'gene chip development technology,' and has successfully developed productions against hypertension."

We can see distortion and filtering in media in this case, as *National Business Daily* reports only that the research team is led by a famous scientist and owns impressive technologies, ignoring its R&D expenses, the economic value of its patents, and the possibility that the participation of Honghao Zhou is only nominal scientist. After querying the database, we find that Hong Hao Ji Yin has not been granted a patent since M&A announcement. We also find that its sales and earnings decreased overall from 2014 to 2019.

We then check the content of the enquiries and replies between the CSRC and Qian Shan Yao Ji in 2017. In the enquiries and replies, Qian Shan Yao Ji explains, "The decline in sales and earnings of Hong Hao Ji Yin is due to the change in sales method. Before 2016, the products were mainly sold by dealers, and after 2017, the products were mainly directly sold by our company … Under the background of the 'two-invoice system' policy [health care reform in China in 2017], the profits of the dealers cooperating with Hong Hao Ji Yin declined, the enthusiasm of the dealers also decreased, and the willingness and intensity of clinical and academic publicity in hospitals declined … The customers of the products are Xiangya Hospital of Central South University, the Second Xiangya Hospital of Central South University, the First People's Hospital of Huaihua Hospital, Guangzhou First People's Hospital, Fujian Provincial Hospital, etc." From the enquiries and replies, we find that Hong Hao Ji Yin states that the popularity of its products is greatly influenced by sales methods, not technology. We also find that Honghao Zhou (Director, Institute of Clinical Pharmacology, Central South University) has strong work connections and geographic connections with hospitals.

Six years after the completion of the merger, the chairman of Qian Shan Yao Ji was banned for life from entering the capital market by the CSRC for financial fraud, Qian Shan Yao Ji was delisted, and investors who bet on Hong Hao Ji Yin suffered big losses.

Sales and Earnings of Hong Hao Ji Yin, 2014–2019

	2014	2015	2016	2017	2018	2019
Sales	23,138,461.54	86,412,307.69	54,814,068.66	3,965,568.06	729,307.73	619,150.86
Earnings	16,379,597.33	58,909,351.69	22,866,922.11	-26,403,824.09	-35,922,697.45	-34,618,572.83

Appendix 2: A Theoretic Model of Media Sentiment Bias of Innovation

We model the impact of media sentiment bias of innovation on investor preferences in relation to technology M&As. We assume that investor preferences for technology M&As (buying acquirer's stock) depend on investor preferences for innovation type (e.g., biotech, new energy, or chip manufacturing) and the target's innovation productivity.

Setup. Media reports a technology M&A, and the innovation type of the target is arbitrary. Although the innovation type of the target is known, the target's innovation productivity is unknown, and news are the main basis for estimation. The true innovation productivity of period-t target is C_t, which is distributed normally with mean C_0 and precision σ_C: $C_t \sim N(C_0, 1/\sigma_C)$.

Media observes C_t and reports media sentiment of innovation $M_t = C_t + B$, where B is the time-invariant degree of media sentiment bias of innovation, drawn from the distribution $N(B_0, 1/\sigma_B)$. Media with positive B provide a more favorable interpretation of the target's innovation productivity; the converse is true for media with negative B. Investors learn about bias B over time from the sequence of news.

After observing news on a technology M&A from period 1 to period T, investors decide whether to buy the acquirer's stock in period T. The investment is based on the estimated innovation productivity of the period-T target, as well as on investor innovation preferences. Investors buy the acquirer's stock in period T if $\hat{C}_T + \alpha > C_0$, where $\hat{C}_T$ is the investors' estimate of innovation productivity of the period-T target, and α is the investors' preference of innovation type (α can be positive or negative). Innovation preference α is heterogeneous, with a continuum of investors, cumulative distribution function $F(\alpha)$, and probability density function $f(\alpha) > 0$ for all α. Investors are homogeneous in their updating about B and C.

Signal extraction. Investors face a signal extraction problem. On observing M_t, they make inferences with respect to the C_t and B. A positive M_t may be due to a highly innovative target or to bias. After observing T media reports with average $\overline{M_T} = \sum_{t=1}^{T} M_t/T$, given the normal distribution of the signals, the investors estimate the bias to be:

$$\hat{B}_T = \frac{\sigma_B B_0 - T\sigma_C C_0 + T\sigma_C \overline{M_T}}{\sigma_B + T\sigma_C}.$$

Estimation of $\hat{B}_T$. $\overline{M_T} = \sum_{t=1}^{T} M_t/T = \sum_{t=1}^{T}(C_t + B)/T = \sum_{t=1}^{T} C_t/T + B \sim N\left(C_0 + B_0, \frac{1}{T\sigma_C} + \frac{1}{\sigma_B}\right)$. According to formulas (4), (5), (8), and (9) of Pollock (2006), we obtain the following expression of $\hat{B}_T$:

$$\begin{aligned}\hat{B}_T = E[B|\overline{M_T}] &= E[B] + \frac{COV(B, \sum_{t=1}^{T} C_t/T + B)}{Var(\sum_{t=1}^{T} C_t/T) + Var(B)}\left(\overline{M_T} - E(\overline{M_T})\right)\\ &= B_0 + \frac{T\sigma_C}{\sigma_B + T\sigma_C}(\overline{M_T} - B_0 - C_0)\\ &= \frac{\sigma_B B_0 - T\sigma_C C_0 + T\sigma_C \overline{M_T}}{\sigma_B + T\sigma_C}.\end{aligned}$$

Using this estimate of bias, rational investors estimate $\hat{C}_T$. They subtract the $\hat{B}_T$ from M_T and combine it in a precision-weighted average with the prior about C_T, i.e., C_0. Hence,

$$\hat{C}_T = \frac{\sigma_C \times C_0 + W[M_T - \hat{B}_T]}{\sigma_C + W}$$

where W, the precision of $M_T - \hat{B}_T$, equals $(\sigma_B + T\sigma_C)^2/(\sigma_B + (T-1)\sigma_C)$.

Calculation of W. We calculate the precision W of the preliminary estimate $M_T - \hat{B}_T$, which is a rational investors' expectation of the innovation productivity of the target.

$$\begin{aligned}\hat{C}_T^P &= \frac{M_T[\sigma_B + T\sigma_C]}{\sigma_B + T\sigma_C} - \frac{\sigma_B B_0 - T\sigma_C C_0 + \sigma_C \sum_{t=1}^{T} M_t}{\sigma_B + T\sigma_C}\\ &= \frac{\sigma_B}{\sigma_B + T\sigma_C}(B - B_0) + \frac{\sigma_B + (T-1)\sigma_C}{\sigma_B + T\sigma_C} C_T - \frac{\sigma_C \sum_{t=1}^{T-1} C_t}{\sigma_B + T\sigma_C} + \frac{T\sigma_C C_0}{\sigma_B + T\sigma_C}\end{aligned}$$

where the second step follows from substituting $M_t = C_t + B$ and combining terms. Note that since

$\hat{C}_T^P$ is an estimate of C_T, its variance does not itself depend on C_T but does depend on all other random variables (C_1, ...C_{T-1}, B). We calculate the variance of $\hat{C}_T^P$ to be:

$$\frac{\sigma_B}{(\sigma_B + T\sigma_C)^2} + \frac{(T-1)\sigma_C}{(\sigma_B + T\sigma_C)^2} = W^{-1}$$

where W is the precision of $\hat{C}_T^P$ and is expressed as $W = (\sigma_B + T\sigma_C)^2/(\sigma_B + (T-1)\sigma_C)$.

Estimation of $\hat{C}_T$. Investors form innovation productivity estimate for target $\hat{C}_T$ by taking a precision-weighted average of the prior innovation capability, C_0 with precision σ_C, and an estimated one, $\hat{C}_T^P$ with precision W. Therefore,

$$\hat{C}_T = \frac{\sigma_C \times C_0 + W[M_T - \hat{B}_T]}{\sigma_C + W} = \frac{\sigma_C C_0}{\sigma_C + W} + \frac{W[M_T - \hat{B}_T]}{\sigma_C + W}$$
$$= \frac{\sigma_C C_0}{\sigma_C + W} + \frac{W}{\sigma_C + W}\left[\frac{M_T[\sigma_B + T\sigma_C]}{\sigma_B + T\sigma_C} - \frac{\sigma_B B_0 - T\sigma_C C_0 + \sigma_C \sum_{t=1}^{T} M_t}{\sigma_B + T\sigma_C}\right]$$
$$= \frac{\sigma_C C_0}{\sigma_C + W} + \frac{W}{\sigma_C + W}\left[\frac{\sigma_B}{\sigma_B + T\sigma_C}(B - B_0) + \frac{\sigma_B + (T-1)\sigma_C}{\sigma_B + T\sigma_C} C_T - \frac{\sigma_C \sum_{t=1}^{T-1} C_t}{\sigma_B + T\sigma_C} + \frac{T\sigma_C C_0}{\sigma_B + T\sigma_C}\right]$$

We use Proposition 1 below to summarize the effect of bias B on the estimated innovation productivity of target $\hat{C}_T$, conditional on the realized innovation productivity C_t, $t = 1, \dots, T$.

Proposition 1. For any finite T, (i) an increase in bias B increases the estimated innovation productivity of the target, $\hat{C}_T$: $\partial(\hat{C}_T)/\partial B > 0$, and (ii) in the limit as $T \to \infty$, the effect of bias is zero: $\lim_{T\to\infty} \partial(C_T)/\partial B = 0$.

Proofs of Proposition 1. (i) The proof of Proposition 1 follows immediately from taking derivatives and limits for any finite T: $\partial(\hat{C}_T)/\partial B = \frac{W}{\sigma_C + W}\frac{\sigma_B}{\sigma_B + T\sigma_C} > 0$. (ii) Using the fact that $\lim_{T\to\infty} \frac{W}{\sigma_C + W} = 1$, for infinite T: $\lim_{T\to\infty} \partial(\hat{C}_T)/\partial B = 0$.

The intuition for Proposition 1 is straightforward and predicts two effects of bias B on expected innovation productivity $\hat{C}_T$. First, more hyping on the part of media (higher B) leads to more positive M_T for the period-T target, which leads to a higher perceived $\hat{C}_T$. Second, a higher B is associated with a higher average of past MII $\overline{M_T}$, and therefore higher perceived bias $\hat{B}_T$ leads to a lower perceived $\hat{C}_T$. For finite T, the first, direct effect dominates the second, indirect effect, and hence bias has an impact on beliefs: $\partial(\hat{C}_T)/\partial B > 0$ (Proposition 1.(i)).

As $T \to \infty$, the estimated bias $\hat{B}_T$ converges to the true bias B. Since investors eventually become fully aware of the degree of bias, bias has no effect on the expected perceived innovation productivity as long as investors are rational. The same would be true if bias B were known from the start (Proposition 1.(ii)).

We analyze the impact of bias on investor investment decisions. Investors invest in a technology M&A that contains the period-T target if $\hat{C}_T + \alpha > C_0$. Then, the probability of investing in a technology M&A is $P(\alpha \geq C_0 - \hat{C}_T) = 1 - F(C_0 - \hat{C}_T)$, an increasing function of the estimated innovation productivity $\hat{C}_T$ of target.

Proposition 2 summarizes the effect of bias B on investment probability $1 - F(C_0 - \hat{C}_T)$.

Proposition 2. (i) For any finite T, an increase in bias B increases the probability of investing in a technology M&A $1 - F(C_0 - \hat{C}_T)$: $\partial\left(1 - F(C_0 - \hat{C}_T)\right)/\partial B > 0$, and (ii) in the limit as $T \to \infty$, the effect of media bias is zero.

Proofs of Propositions 2. (i) We use $\partial\left(1 - F(C_0 - \hat{C}_T)\right)/\partial B = f(C_0 - \hat{C}_T) \times \partial(\hat{C}_T)/\partial B$ together with $f(\alpha) > 0$ for all α. (ii) Note that $\lim_{T\to\infty} \partial(\hat{C}_T)/\partial B = 0$ and therefore, since $f(\alpha)$ is bounded, $\lim_{T\to\infty} \partial\left(1 - F(C_0 - \hat{C}_T)\right)/\partial B = 0$.

Appendix 3: Full List of Media Sources Used in Our Study

This table presents publishing activity for media sources in the sample from 2009 to 2021. "News num." is the number of media reports belongs to a certain media source. "Press or Internet firm" is the category of media source, including press and internet firm. "State-controlled or market oriented" is the category of media source, including state-controlled and market-oriented. The state-controlled media is either owned or controlled by the government and nonprofit organizations. The market-oriented media is either owned or controlled by financial institutions, public companies, or wealthy individuals. "National or local" is the category of media source, including national and local. The national-wide media is national release. The local-wide media is province or prefecture-level city release.

Media names	News num.	Press/Internet	State/Market	National/Local
China Securities Journal*	601	Press	State	National
Shanghai Securities News*	509	Press	State	National
Securities Times*	293	Press	State	National
National Business Daily	249	Press	Market	National
Beijing Business Today	68	Press	Market	National
Securities Daily*	61	Press	State	National
Changjiang Times	52	Press	Market	Local
21st Century Business Herald	51	Press	Market	National
Economic Daily	38	Press	State	National
China Business Network	30	Press	Market	National
Jinrongtouzibao	21	Press	Market	National
SINA	19	Internet	Market	National
China Business Journal	18	Press	State	National
JIEMIAN	18	Internet	Market	National
Economic Information Daily	17	Press	State	National
http://www.jrj.com.cn/	16	Internet	Market	National
Netease	15	Internet	Market	National
Capital Week	14	Press	Market	National
Weekly on Stocks	13	Press	Market	National
China Internet Information Center	13	Internet	State	National
International Financial News	13	Press	Market	National
https://www.p5w.net/	12	Internet	Market	National
Shenzhen Economic Daily	11	Press	Market	Local
The Beijing News	11	Press	Market	National
China Economic Herald	11	Press	State	National
Chongqing Economic Times	10	Press	Market	Local
Oriental Morning Post	9	Press	Market	Local
The Economic Observer	8	Press	Market	National
Shandong Business Daily	7	Press	Market	Local
Xinhua	7	Press	State	National
Jiangmen Daily	7	Press	State	Local
Tencent	7	Internet	Market	National
https://www.stockstar.com/	6	Internet	Market	National
Southern Metropolis Daily	6	Press	Market	Local
https://www.gelonghui.com/	6	Internet	Market	National
Caixin Media	6	Internet	Market	National
China Economic Times	5	Press	State	National
https://cnfol.com/	5	Internet	Market	National
Investor Journal	5	Press	Market	National
Cai Jing	5	Internet	Market	National
Enterpreurs' Daily	5	Press	Market	National
https://www.thepaper.cn	5	Internet	Market	National

Chinese Securities Journal	4	Press	Market	National
China Chemical Industry News	4	Press	State	National
Yangchengwanbao	4	Press	State	Local
https://business.sohu.com/	4	Internet	Market	Local
Xinxishibao	4	Press	Market	Local
http://stock.hexun.com/	4	Internet	Market	National
China Electronics News	3	Press	State	National
Dahe Daily	3	Press	Market	Local
Reference News	3	Press	State	National
Chinese Industry&Economy	3	Press	State	National
Chengdu Economic Daily	3	Press	Market	Local
The Time Weekly	3	Press	Market	Local
China Enterprise News	3	Press	State	National
China Industry News	2	Press	State	National
Nanfang Daily	2	Press	State	Local
Daily Business	2	Press	Market	Local
Changshawanbao	2	Press	State	Local
Foshan Daily	2	Press	State	Local
Touzikuaibao	2	Press	Market	Local
Taizhou Business Daily	2	Press	Market	Local
Hong Kong Commercial Daily	2	Press	State	Local
https://www.ifeng.com	2	Internet	Market	National
Henan Business Daily	2	Press	Market	Local
Wabei	2	Internet	Market	National
Xiaoxiang Morning	2	Press	Market	Local
Commercial Times	2	Press	Market	Local
https://www.rednet.cn	2	Internet	State	Local
Wenhuibao	2	Press	State	Local
Modern Express	2	Press	Market	Local
ChinaTimes	2	Press	State	National
Zhejiang Daily	2	Press	State	Local
Western Business Daily	1	Press	Market	Local
China Business News	1	Press	State	National
Guangzhou Daily	1	Press	State	Local
https://lanfucaijing.com/index.php	1	Internet	Market	National
China Financial Times	1	Press	State	Local
http://www.beijingleather.com.cn/	1	Internet	Market	National
Haikou Daily	1	Press	State	Local
China Trade News	1	Press	State	National
Jinjiangjingjibao	1	Press	Market	Local
https://www.gg-led.com/	1	Internet	Market	National
Sanxiangdushibao	1	Press	Market	Local
Construction Times	1	Press	State	National
China Machinery Network	1	Press	Market	National
Guizhou Business News	1	Press	Market	Local
Xinxiang Daily	1	Press	State	Local
Quanzhouwanbao	1	Press	State	Local
https://www.mbcaijing.com/	1	Internet	Market	National
http://www.chinajiceng.com.cn/	1	Internet	State	National
China Jingjiwanbao	1	Press	State	Local
Straight flush	1	Internet	Market	National
https://www.leiphone.com/	1	Internet	Market	National
Beijing Youth Daily	1	Press	State	National
Xiandaiwuliubao	1	Press	State	National

Zhongguohuanjingbao	1	Press	State	National
http://wallstreetcn.com/	1	Internet	Market	National
China Business Network	1	Press	Market	National
Hubei Daily	1	Press	State	Local
https://www.chinanews.com.cn/	1	Internet	State	National
Shenzhen Special Zone Daily	1	Press	Market	Local
China Investment Network	1	Press	State	Local
China Textile News	1	Press	State	National
Huzhou Daily	1	Press	State	Local
China Economic Weekly	1	Press	State	National
Shanghai Business Daily	1	Press	Market	Local
Fuzhou Daily	1	Press	State	Local
Dushixiaofei Morning Post	1	Press	Market	Local
https://www.finet.com.cn/	1	Internet	Market	Local
https://www.chinabuses.com	1	Internet	Market	National
Xinminwanbao	1	Press	State	Local
Chongqing Daily	1	Press	State	Local
Wenzhou Business Daily	1	Press	Market	Local
Private Economy News	1	Press	Market	Local
Innovative Finance Observation	1	Press	Market	Local
Total	2407	87/29	49/67	66/50

Appendix 4: Detailed Classifications of Innovation Keywords

Keywords used to identify the investment in innovation include research center (yan2jiu1zhong1xin1), R&D direction (yan2fa1fang1xiang4), R&D field (yan2fa1ling3yu4), R&D concept (yan2fa1li3nian4), R&D project (yan2fa1xiang4mu4), R&D cycle (yan2fa1zhou1qi1), R&D team (yan2fa1tuan2dui4), technical team (ji4shu4tuan2dui4), R&D system (yan2fa1ti3xi4), R&D resource (yan2fa1zi1yuan2), R&D staff (yan2fa1ren2yuan2), R&D investment (yan2fa1tou2ru4), R&D effect (yan2fa1xiao4guo3), R&D center (yan2fa1zhong1xin1), R&D experience (yan2fa1jing1yan4), R&D platform (yan2fa1ping2tai2), R&D design (yan2fa1she4ji4), R&D pipeline (yan2fa1guan3xian4), technological transformation (ji4shu4gai3zao4), research expense (ke1yan2fei4yong4), R&D expense (yan2fa1fei4yong4), in the study (zai4yan2), clinical trial (lin2chuang2shi4yan4), technology platform (ji4shu4ping2tai2), technicians (ji4shu4ren2yuan2), scientist (ke1xue2jia1), education (xue2li4), undergraduate (ben3ke1), master (shuo4shi4), doctor (bo2shi4), postdoctoral (bo2shi4hou4, bo2hou4), expert (zhuan1jia1), professor (jiao4shou4), researcher (yan2jiu1yuan2), and inventor (fa1ming2ren2).

Keywords used to identify the cooperation of innovation include academic seminar (xue2shu4yan2tao3hui4), academic conference (xue2shu4hui4yi4), summit (gao1feng1lun4tan2), research institute (yan2jiu1ji1gou4, ke1yan2yuan4suo3, yan2jiu1yuan4, yan2jiu1suo3), research laboratory (yan2jiu1shi4), university (da4xue2, gao1xiao4), college (xue2yuan4), and society (xue2hui4).

Keywords used to identify the outcomes of innovation include invention (fa1ming2), patent (zhuan1li4), journal (qi1kan1), paper (lun4wen2), research appraisal (cheng2guo3jian4ding4), R&D income (yan2fa1shou1ru4), production technology (sheng1chan3gong1yi4, sheng1chan3ji4shu4, zhi4zuo4gong1yi4), research outcome (yan2fa1cheng2guo3), and innovative product (chuang4xin2chan2pin3).

Keywords used to identify the generalization of innovation include research technology (yan2zhi4ji4shu4), core technology (he2xin1ji4shu4), key technology (guan1jian4ji4shu4), technology advantage (ji4shu4you1shi4), advanced technology (ji4shu4xian1jin4), technology threshold (ji4shu4men2kan3), technology accumulation (ji4shu4ji1lei3, ji4shu4ji1dian4), technological level (ji4shu4shui3ping2), import substitution (jin4kou3ti4dai4), high-tech company (gao1xin1ji4shu4qi3ye4), exploit (kai1fa1), research (yan2fa1), innovation (chuang4xin1), and design (she4ji4).

Appendix 5: Definitions and Calculations of All Variables

Variables	Definition	Calculation
$CARs$	Cumulative abnormal return	The sum of the abnormal returns estimated as the difference between real and predicted returns using the Fama–French three-factor model during the [-5, 5] window.
$VBHARs_{12}$	Value-weighted buy-and-hold abnormal return	Buy and holding abnormal returns which are calculated for each acquirer as follows: $BHARs_{i,T} = \prod_{t=0}^{T}(1 + R_{i,t}) - \prod_{t=0}^{T}(1 + R_{benchmark,t})$, where $R_{i,t}$ is the stock return of stock i in month t, benchmark is the returns of the 25 value-weighted, non-rebalanced portfolios grouped by both firm size and book-to-market ratio.
$EBHARs_{12}$	Equally-weighted buy-and-hold abnormal return	Buy and holding abnormal returns which are calculated for each acquirer as follows: $BHARs_{i,T} = \prod_{t=0}^{T}(1 + R_{i,t}) - \prod_{t=0}^{T}(1 + R_{benchmark,t})$, where $R_{i,t}$ is the stock return of stock i in month t, benchmark is the returns of the 25 equally-weighted, non-rebalanced portfolios grouped by both firm size and book-to-market ratio.
$PostIP_i$	Target's post-announcement invention patent counts	Log (1+target's number of newly granted invention patents i years (i= 1, 2, and 3) after the announcement date.
$PostUP_i$	Target's post-announcement utility patent counts	Log (1+target's number of newly granted utility patents i years (i= 1, 2, and 3) after the announcement date.
$MedSI$	Media sentiment of innovation	We first calculate the innovation keywords ratio of a media report by dividing the number of innovation keywords only related to target's innovation productivity by the total number of words (in thousands) in a media report. The innovation keywords ratio of a report is then multiplied by the sentiment of a report. Finally, we take the average of the values of all media reports in a technology M&A.
$AnaSI$	Analyst sentiment of innovation	We divide the number of innovation keywords which is only related to target's innovation productivity by the total number of words (in thousands) in an analyst report. The innovation keywords ratio of an analyst report is then multiplied by the sentiment of an analyst report. We take the average of the values of all analyst reports for each technology M&A.
$AnnSI$	M&As announcements sentiment of innovation (both Purpose of Transaction Section and Target's Competitive Advantages Section)	1) We divide the number of innovation keywords related to target's innovation productivity by the total number of words (in thousands) in both POT and TCA Sections of M&As announcements. 2) We calculate the innovation keywords ratio of both POT and TCA Sections of M&A announcements multiplied by their sentiment.
IP	Invention patents	Log (1+ the number of target's granted invention patents disclosed in M&As announcements).
UP	Utility patents	Log (1+ the number of target's granted utility patents disclosed

		in M&As announcements).
$Size\_Acq$	Acquirer's Size	
ROA_Acq	Acquirer's ROA	
MB_Acq	Acquirer's market-to-book ratio	The market value of equity divided by book value at the end of the year before M&A announcement date.
Liq_Acq	Acquirer's liquidity	The cash and equivalents scaled by total assets at the end of the year before M&As announcements date.
Lev_Acq	Acquirer's leverage	The book value of debt over the sum of book value of debt and market value of equity at the end of the year before M&As announcements date.
$Top1\_Acq$	Acquirer's top1 shareholding	The shareholding ratio of the largest shareholder at the end of the year before M&A announcement date.
Age_Acq	Acquirer's age.	The number of years since the listed company goes public at the end of the year before M&As announcements date.
$BrdSize\_Acq$	Acquirer's board size	Log (1+the number of members in board at the end of the year before M&As announcements date).
$IndSize\_Acq$	Acquirer's board independence	The number of independent directors on board at the end of the year before M&As announcements date.
$Equity$	Acquirer's payment method	Dummy variable, if deals financed with equity, value 1, otherwise, value 0.
$RelVal$	Relative size	The ratio of deal value to acquirers' market value as relative size.
$RunUp\_Acq$	Acquirer's past 12-month abnormal return.	Dummy indicator if a firm's runup net market is in the top 10% of all firms' runup net market. Runup net market is the *BHARs* excess hs300 index on the acquirer's stock for pre-acquisition one-year period (years t−1 and t) before the suspension date or announcement date.
SOE_Acq	State-owned	Dummy indicator for state-owned enterprise
Lev_Tar	Target's leverage	The cash and equivalents scaled by total assets at the end of the year before M&As announcements date.
$Size\_Tar$	Target's size	Log (the market value of the target at the end of the year before M&As announcements date).
$TobinQ\_Tar$	Target's Tobin's Q	Log (the ratio of the target's market value divided by the target's total assets).
ROA_Tar	Target's ROA	The EBIT scaled by total assets at the end of the year before M&As announcements date.

Appendix 6: Correlation Matrix

	CAR	$VBHAR_{12}$	$EBHAR_{12}$	$PostIP_1$	$PostIP_2$	$PostIP_3$	$PostUP_1$	$PostUP_2$	$PostUP_3$	$MedSI$	$AnaSI$	$AnnSI$	IP	UP
$VBHAR_{12}$	0.358***													
$EBHAR_{12}$	0.413***	0.945***												
$PostIP_1$	0.070	0.092**	0.088*											
$PostIP_2$	0.068	0.088**	0.091**	0.943***										
$PostIP_3$	0.088**	0.087*	0.094**	0.905***	0.969***									
$PostUP_1$	-0.013	0.005	-0.009	0.241***	0.231***	0.221***								
$PostUP_2$	-0.014	0.005	-0.007	0.191***	0.205***	0.200***	0.890***							
$PostUP_3$	0.006	0.034	0.030	0.167***	0.192***	0.200***	0.835***	0.950***						
$MedSI$	0.122***	0.038	0.040	0.037	0.033	0.035	0.089**	0.071	0.091**					
$AnaSI$	0.013	0.038	0.004	0.128***	0.135***	0.151***	-0.065	-0.056	-0.056	0.127***				
$AnnSI$	-0.023	-0.013	-0.007	0.019	0.029	0.023	0.091**	0.087*	0.102**	0.225***	0.064			
IP	0.004	0.074*	0.056	0.545***	0.555***	0.530***	0.023	0.004	-0.018	-0.036	0.121***	0.057		
UP	0.011	-0.015	-0.017	0.047	0.065	0.062	0.542***	0.576***	0.581***	0.123***	-0.081*	0.105**	0.089**	
$Size\_Acq$	-0.076*	-0.048	-0.113**	0.243***	0.232***	0.225***	0.045	0.020	0.002	-0.108**	0.152***	-0.130***	0.347***	-0.008
ROA_Acq	-0.008	0.052	0.041	0.076*	0.069	0.065	-0.049	-0.058	-0.033	0.080*	0.062	-0.038	0.048	-0.132***
MB_Acq	-0.224***	-0.030	-0.052	-0.106**	-0.112**	-0.128***	-0.010	0.004	-0.023	0.057	0.112**	0.049	-0.049	-0.036
Liq_Acq	0.041	0.091**	0.095**	-0.000	-0.021	-0.018	-0.085*	-0.086*	-0.060	0.149***	0.013	0.068	-0.127***	-0.102**
Lev_Acq	-0.038	-0.119***	-0.131***	-0.011	-0.002	0.009	0.052	0.057	0.040	-0.162***	0.066	-0.049	0.136***	0.107**
$Top1\_Acq$	0.040	0.028	0.042	0.093**	0.079*	0.077*	0.004	0.028	0.022	0.055	-0.035	0.024	0.047	0.032
Age_Acq	0.046	-0.070	-0.092**	0.078*	0.077*	0.078*	-0.046	-0.067	-0.092**	-0.163***	0.010	-0.136***	0.126***	-0.018
$BrdSize\_Acq$	0.008	-0.011	-0.016	0.026	0.046	0.050	0.023	0.022	0.015	-0.015	-0.020	-0.073	0.026	-0.002
$IndSize\_Acq$	-0.043	-0.019	-0.030	0.004	-0.041	-0.043	-0.018	-0.017	-0.032	-0.022	0.045	0.031	-0.023	-0.024
$Equity$	0.068	-0.004	0.017	-0.047	-0.043	-0.040	0.074*	0.113**	0.124***	0.114**	-0.070	0.048	-0.117***	0.115***
$RelVal$	0.258***	0.076*	0.113**	0.141***	0.142***	0.146***	0.041	0.028	0.020	-0.043	-0.066	-0.019	0.059	0.037
$RunUp\_Acq$	-0.273***	-0.050	-0.043	0.009	-0.005	-0.005	0.032	0.000	0.016	0.082*	-0.067	0.049	-0.049	0.001
SOE_Acq	0.010	-0.082*	-0.109**	0.127***	0.111**	0.106**	-0.025	-0.033	-0.043	-0.080*	-0.013	-0.036	0.075*	0.001
Lev_Tar	-0.039	-0.068	-0.052	0.041	0.049	0.053	0.104**	0.103**	0.109**	-0.068	-0.008	-0.053	0.003	0.068
$Size\_Tar$	0.015	0.032	-0.000	0.311***	0.304***	0.292***	0.069	0.055	0.022	-0.083*	0.134***	-0.082*	0.364***	-0.004
$TobinQ\_Tar$	0.054	0.072	0.067	-0.073	-0.055	-0.057	-0.045	-0.028	-0.035	0.172***	0.154***	0.136***	-0.140***	-0.136***
ROA_Tar	-0.034	-0.022	-0.004	-0.028	-0.026	-0.029	-0.090**	-0.068	-0.062	0.036	-0.010	0.053	-0.078*	-0.085*

	$Size\_Acq$	ROA_Acq	MB_Acq	Liq_Acq	Lev_Acq	$Top1\_Acq$	Age_Acq	$BrdSize\_Acq$	$IndSize\_Acq$	$Equity$	$RelVal$	$RunUp\_Acq$	SOE_Acq	Lev_Tar	$Size\_Tar$	$TobinQ\_Tar$
ROA_Acq	-0.004															
MB_Acq	-0.383***	0.091**														
Liq_Acq	-0.261***	0.169***	0.059													
Lev_Acq	0.461***	-0.219***	0.046	-0.498***												
$Top1\_Acq$	0.005	0.110**	-0.065	0.065	-0.018											
Age_Acq	0.476***	-0.250***	-0.137***	-0.329***	0.401***	-0.210***										
$BrdSize\_Acq$	0.186***	-0.004	-0.081*	-0.017	0.148***	-0.055	0.090**									
$IndSize\_Acq$	-0.062	-0.026	0.070	0.002	-0.051	0.096**	-0.003	-0.662***								
$Equity$	-0.219***	0.009	0.049	-0.021	-0.064	-0.008	-0.121***	0.037	-0.035							
$RelVal$	-0.056	-0.119***	-0.206***	-0.125***	0.066	0.002	0.149***	-0.078*	0.076*	0.201***						
$RunUp\_Acq$	-0.184***	0.109**	0.126***	0.077*	-0.118***	0.022	-0.301***	-0.078*	0.022	0.102**	-0.015					
SOE_Acq	0.233***	-0.055	-0.100**	-0.132***	0.262***	0.001	0.430***	0.203***	-0.059	0.002	0.075*	-0.097**				
Lev_Tar	0.103**	0.030	-0.047	-0.049	0.099**	0.082*	0.053	0.055	0.009	-0.141***	-0.013	-0.047	0.115***			
$Size\_Tar$	0.527***	0.017	-0.101**	-0.159***	0.138***	-0.003	0.363***	0.011	0.041	0.059	0.498***	-0.056	0.120***	-0.048		
$TobinQ\_Tar$	-0.235***	0.041	0.241***	0.094**	-0.180***	-0.056	-0.190***	-0.096**	0.073	0.195***	0.012	0.166***	-0.163***	-0.265***	0.113**	
ROA_Tar	-0.072	0.070	0.030	0.076*	-0.148***	-0.011	-0.091**	0.042	-0.008	0.055	-0.071	0.019	-0.036	-0.235***	-0.031	0.409***

Appendix 7: Media Sentiment Prediction and Bias of Innovation

This table reports the multivariate regression of media sentiment of innovation ($MedSI$) on acquirer's, target's fundamentals. We decompose media sentiment of innovation into the expected portion and the unexpected portion using regression model (3) reported in Section 4.3. Prediction of media sentiment of innovation is the expected portion ($MedPred$). Media sentiment bias of innovation ($MedBias$) is the unexpected portion. All variables are as defined in Appendix 5. The sample period is from 2009 to 2021. The *t*-statistics shown in parentheses are based on standard errors adjusted for heteroscedasticity. Significance at the 1%, 5%, or 10% level is indicated by ***, **, or *, respectively.

Panel A:	$MedSI$
IP	0.017
	(0.20)
UP	0.277***
	(4.09)
$Size\_Acq$	0.275
	(1.60)
ROA_Acq	1.348
	(0.86)
MB_Acq	0.021
	(0.58)
Liq_Acq	1.187
	(1.32)
Lev_Acq	-2.023***
	(-2.67)
Lev_Tar	-0.572
	(-1.33)
$Size\_Tar$	-0.299**
	(-2.23)
$TobinQ\_Tar$	0.414***
	(3.33)
ROA_Tar	-1.129
	(-1.38)
Cons	1.738
	(0.46)
Industry FE	Yes
Year FE	Yes
N	498
Adjusted R^2	0.15

Panel B:

Variable	Sample	Mean	SD	Min.	Median	Max.
$MedPred$	498	2.60	0.897	-0.69	2.66	5.43
$MedBias$	498	-0.00	2.130	-3.64	-0.34	9.78