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RESEARCH ARTICLE

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Digital platforms in the news industry: how social media platforms impact traditional media news viewership

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ABSTRACT
We examine how social media plays the role of an attention driver for traditional media. Social media attracts and channels attention to a topic. This attention triggers people to seek further information that is reported professionally in traditional media. Specifically, the volume of social media posts about a stock influences the attention to this stock the next day, proxied by the viewership of news articles on the same stock published the next day. We test this hypothesis in the stock market context because social media is less likely than traditional media to diffuse fundamental information in the stock market. Analysing stock-related news articles and stock-related social media posts from Sina Finance and Sina Weibo, we find that the social media post volume of a stock at time *t-1* is associated with the traditional media viewership of the same stock at time *t*. This effect is amplified when social media sentiment about the stock is more intense or positive, and with an increase in the volume of verified social media posts about the stock. Our results provide evidence that social media platforms act as attention drivers, which differ from the information channel functions discussed in prior literature.

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Digital platforms; social media; traditional media; news viewership; financial news; stock market

1. Introduction

Recently, the European Union (EU) proposed legislation calling for social media platforms to compensate traditional media[1] for embedding news articles in their feeds.[2] This idea is based on two assumptions: 1) both social media and traditional media provide the same service, i.e., they are both information channels, and 2) the relationship between social media and traditional media is competitive – social media platforms can harm traditional media as readers increasingly use social media as their main source of news consumption, thereby significantly reducing traditional media viewership. However, the relationship between social media and traditional media could also be complementary. For example, Sismeiro and Mahmood (2018) found that during a Facebook outage, there was a significant drop in visits to traditional media sites. Bar-Gill et al. (2020) found that the impact of Facebook recommendations on traditional media viewership was higher than email newsletters. That is, in scenarios where information is diffused via both social media and traditional media, social media is often positively associated with the viewership of traditional media.

In this paper, we question the first assumption about both social and traditional media providing the same service. We argue that not only does social media play the role of an information channel, but it also serves as an attention driver for traditional media. Social media posts that contain noisy information are also positively correlated with traditional media viewership. Such a mechanism can be seen in incidents where social media attracts attention to a topic, and the attention results in higher viewership for news articles that provide further details about the same topic. For example, in April 2016, the former chairman of a famous candy company "Guanshengyuan (冠生园)", when visiting a tourist spot, was killed by a monkey sitting in a tree accidentally dropping a stone on him. The event catalysed intense social media discussions about the company (shown in Table A1 in the Appendix). The improbable incident itself was irrelevant to the stock's fundamentals. The chairman had retired from the company several years prior to the incident and had no subsequent role in the company. However, the next day investors that were unaware of the company started looking up information about it, and news articles about the company were listed on traditional media sites as the top viewed news articles. Table A1 in the Appendix provides the Baidu Search Index of "Guanshengyuan" in April 2016.

Given the outsized role social media plays in directing public attention, our goal is to answer two specific research questions: 1) Does social media volume affect news viewership, as a proxy for attention? 2) How do

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social media post characteristics such as social media sentiment (intensity and positivity) and the source verifiability of social media posts moderate the impact of social media volume on news viewership? We hypothesise that social media volume is positively associated with traditional media viewership. Specifically, we argue that social media drives people's attention to a topic and such attention makes individuals likely to seek out and read detailed information on this topic in traditional media . That is, social media posts at time *t-1* can influence the viewership of traditional media at time *t*.[3] Following previous literature (Ren & Nickerson, 2019; Shu et al., 2019; Stieglitz & Dang-Xuan, 2013; Tian et al., 2018), we argue that the intensity and positivity of social media sentiment, as well as the source verifiability of social media posts, positively moderate the effect of social media volume on traditional media viewership.

We test our hypotheses in the context of the Chinese stock market. China was the second largest stock market in terms of both trading volume and market capitalisation during our sample period. China's stock market is increasingly becoming the focus of researchers and investors (Carpenter et al., 2021). The Chinese stock market is an apt context to investigate the interaction for two reasons. The first reason is the primacy of traditional media in reporting information about the stock market. According to Chinese laws, any information that affects stock returns should be published in the designated traditional media first. That is, social media posts at time *t-1* cannot include new information from traditional media at time *t*. This rules out the possibility that our results may be driven by social media platforms serving as information channels, and consequently allay concerns about endogeneity. Second, a fundamental difference between the Chinese and US markets is that individual investors dominate the Chinese market, while institutional investors are the main players in the US market. According to China Securities Depository and Clearing Corporation Limited, more than 99.7% of investors in the Chinese stock market were individuals at the end of 2019. Given that most social media users are individuals, we expect social media to play a pronounced role in the Chinese market.

We use two databases, Sina Finance and Sina Weibo, corresponding respectively to traditional media and social media. Sina Finance is a digital news platform in China that contains almost all public financial information about the Chinese stock market as reported by traditional media. Sina Weibo is a microblogging service (similar to Twitter, so a weibo in China is analogous to a tweet). Our dataset includes about 1.4 million stock news stories and about 50 million stock-related weibos.

We estimated fixed effects models with news article viewership as the dependent variable and social media post volume as the independent variable. Moderators include a) social media post intensity, b) social media information sentiment, and c) social media post verifiability. Control variables include c) stock performance, d) news article viewership on the prior day, and e) news article volume on the present day. Our results show that the social media volume about a stock at time *t-1* is positively associated with the viewership of traditional media about the same stock at time *t*; this effect is amplified when social media sentiment about this stock is more intense or positive, or when there is an increase in social media posts about this stock by verified account holders.

To provide additional support for the causal relationship, we conducted several causality tests. First, following Ren et al. (2021), we conducted the analysis using observations where there is no news article from *t-7* to *t-1* to control for the influence of outdated information. Second, following Garcia (2013) and Siganos et al. (2014), we repeated the analysis using only the Monday samples to control for unobservable variables. Third, to exclude a conflating mechanism in which our results are driven by returns at *t*, we reran our regressions using samples when there is no stock return at *t* (e.g., weekends or national holidays samples). Finally, as Deng et al. (2018) and Dewan and Ramaprasad (2014) did in similar contexts, we used Granger causality tests that account for bidirectional relationships. Social media information volume and news article viewership Granger-cause each other, with a larger effect for social media information volume Granger-causing news article viewership. Moreover, we used an additional dataset obtained later from Sina.com and reported the descriptive analysis of the sources of visits to news articles in traditional media. Our descriptive result shows that traffic primarily goes from social media to traditional media. We find that up to 40% of visits to news articles in traditional media come from activities in social media. The contextually appropriate setting of the stock market and the Granger causality tests allow us to interpret our results in a clear manner.

This paper makes two contributions to the literature. First, we propose a different role for social media and provide evidence that social media is an attention driver. This role differs from the conventional view that social media serves only as an information channel that disseminates basic information, misinformation, or feedback information (Allcott & Gentzkow, 2017; Castillo et al., Forthcoming; Chen et al., 2014;

Dellarocas, 2003). It is also useful to explain some phenomena documented in the literature (e.g., social media-driven customer engagement in Castillo et al. (2021) and social media-driven product awareness in Duan et al. (2008)). Second, our results contribute to an emerging strand of literature on the ongoing debate of whether social media platforms benefit or harm traditional media (Sismeiro & Mahmood, 2018). We argue for a different mechanism in which social media and traditional media do not necessarily compete for individual viewership. Our results suggest that social media can be beneficial to traditional media by drawing attention to news in traditional media.

The remainder of this paper is organised as follows. The next section presents the conceptual foundation and hypotheses development for our work. We then explain the data in Section 3, report our methodology and present our results, robustness checks, and causality tests in Section 4. In Section 5, we summarise the results and discuss implications before highlighting limitations and opportunities for future research. Our concluding remarks follow in Section 6.

2. Conceptual foundation and hypotheses development

2.1. Social media

2.1.1. Social media as information channel

Social media platforms generate and disseminate user-generated content. There is a consensus that a key feature of social media is the dissemination of information. As Standage (2013, p. 3) puts it, social media is "an environment in which information is passed from one person to another along social connections … " An important characteristic of social media is that it enables bidirectional communication (Dellarocas, 2003).

Previous studies are mainly concerned with what information social media disseminates. More specifically, whether social media spreads legitimate information (e.g., fundamental information about stocks in the stock market) or misinformation (e.g., rumours or "fake news"). For example, Clarke et al. (2020) and Vosoughi et al. (2018) find that fake news spreads faster than real news. Several studies (Bae et al., 2021; Schuetz et al., 2021) investigate how to combat infodemics during the current COVID-19 pandemic. On the other hand, Chen et al. (2014) and Luo et al. (2013) argue that social media disseminates fundamental information in the stock market that has not been incorporated into the stock market. Hu et al. (2015) argue that social media disseminates information that can create online social value.

Some studies take a different argument and consider information that includes sentiment. For example, Deng et al. (2018) show that investor sentiment expressed in social media Granger-causes stock returns. These authors find a bidirectional influence between social media and stock returns. Many financial studies also use social media sentiment as a proxy for investor sentiment (see, for example, Antweiler & Frank, 2004; Dong & Gil-Bazo, 2020; Siganos et al., 2014; Sprenger et al., 2014). These studies implicitly assume that sentiment is a type of information and is disseminated through social media.

2.1.2. Social media and traditional media

When social media platforms disseminate information, the question naturally arises as to what the differences are between social media and traditional media. A handful of studies have examined which media has a greater impact. For example, Dong et al. (2022) show that social media predicts absolute stock returns for a longer interval (from $t + 2$ to $t + 10$); traditional media is predictive for the next day. Dewan and Ramaprasad (2014) compare social media and traditional media in terms of their impact on music sales and find that traditional media can help music sales, but social media can hurt sales, especially song sales. Y. Y. Yu et al. (2013) find that social media has a stronger relationship with stock performance than traditional media. Dong et al. (2022) document that social media and traditional media have different content and can be useful in different ways. Specifically, these authors argue that social media focuses on a small amount of information, while traditional media covers more diverse information about the stock market.

Some other studies focus on their relationship, i.e., does the advent of social media hurt traditional media? Sismeiro and Mahmood (2018) show that during a Facebook outage, there was a significant decrease in visits to traditional media sites. Bar-Gill et al. (2020) compare the impact of Facebook recommendations versus email newsletters on traditional media viewership. Both studies support the argument that social media is positively related to traditional media's viewership and their relationship is complementary, not competitive as assumed by regulators. Jiao et al. (2020) find that the impact of traditional media on stock volatility and turnover is different from that of social media. They further argue that social media repeats information from traditional media.

An important starting point of previous studies is to treat social media as an information channel, like traditional media. Our paper does not make this assumption and instead considers if social media may serve a different role in the decision-making process. In particular, our paper makes two contributions: 1. We show evidence that social media serves as an attention driver, which was not explicitly documented in the previous literature. The new mechanism is useful for explaining many phenomena in the literature; 2. By introducing the new mechanism, we extend the literature on the association between social media and mass media, and describe implications for policy makers.

2.2. Social media as attention driver

In this section, we argue that social media is an attention driver. Readers may be aware of some topics that are circulated on social media, and subsequently search related fundamental information. That is, even if when social media only contains non-fundamental information, it is also eventually associated with fundamental information diffusion.

This argument is motivated by many phenomena documented by previous studies. For example, Duan et al. (2008) document an interesting phenomenon: ratings of online user reviews are not statistically related to movie box office revenues; however, the volume of online postings affects box office sales. They interpret this phenomenon to mean that online user reviews increase product awareness. Castillo et al. (2021) documented that social media-driven pre-consumption customer engagement and box office revenues on opening weekend are positively related. One possible explanation for this result is that social media platforms increase customer attention even though social media posts prior to consumption are plausibly relatively less informative messages.

Limited studies explicitly argue the attention driver role of social media. In particular, a recent study discusses attention spillovers (Zhu et al., 2020), following up on previous work on social media spillovers (Aral et al., 2013). Zhu et al. (2020) explore how the attention that a Wikipedia article attracts can spill over to other articles to which that article links, and suggest that Wikipedia articles can draw attention to downstream linked articles. Carmi et al. (2017) document that an increase in attention, proxied by the external demand shocks like recommendations from the Oprah Winfrey television show and the New York Times, spills over into product recommendation networks like Amazon.com.

Our paper is different from the previous literature. The previous studies focused on the attention spillover *within* the social media network. Our paper extends this body of literature and examines how attention spills over from social media to traditional media.

2.3. Social media post volume

Social media post volume can be seen as an indication of a stock's popularity. That is, a herding phenomenon is likely to occur (Dong et al., 2022; Sabherwal et al., 2011) as investors pay more attention to stocks that are popular (Kim et al., 2022).

Previous literature considers social media volume as a proxy for attention, explicitly or implicitly. For example, when indicators of online reviews have been studied to understand their influence on product sales (e.g., Dellarocas et al., 2007; Duan et al., 2008; Kordrostami et al., 2020), the volume of online reviews has been found to increase attention to the product. L. L. L. L. Yu et al. (2015) found that the volume of tweets is strongly correlated with trending time, suggesting that a topic is popular when it is tweeted by many people. Jungherr et al. (2016) used mentions of political figures on Twitter as a measure of public attention towards politics. Knight (2014) claimed that social media mentions represent online attention and act as early predictors of the impact of scholarly research in a given field. Without referring to a specific setting, Mathioudakis et al. (2010) argued that the amount of information commented on, tagged, and created on social media platforms indicates emerging events, breaking news, and information that attracts a large number of people and thus represents crowd attention. Accordingly, they also used a statistical model to identify attention-grabbing items on social media platforms. In practice, many social media platforms use the volume of crowd opinions to indicate the "hotness" of a topic, person, or event: Twitter uses the volume of relevant tweets as an important factor in determining the popularity of trending topics on Twitter (Twitter Trends). Consequently, we propose the following hypothesis:

H1. The volume of social media posts about a stock at time t-1 is positively associated with the viewership of news articles on the same stock at time t.

2.4. Social media post sentiment and source verifiability as moderators

We argue that other characteristics of social media posts that have been explored in previous literature may moderate the impact of social media post volume on traditional media viewership. In the past, scholars have focused on sentiment and source verifiability in addition to social media volume. Some scholars have focused on text-mining these posts to examine how they were written (e.g., sentiment). Others have focused on the details of social media posts to understand who wrote them (e.g., source verifiability).

In this paper, we consider other characteristics of social media posts as moderators. Specifically, we argue that the sentiment intensity, sentiment polarity (positive versus negative), and source verifiability of social media posts can moderate the relationship between social media volume and traditional media viewership. In the following subsections, we provide more details.

2.4.1. Social media post sentiment intensity

tian et al. (2018) used sentiment intensity and polarity as the two aspects of sentiment. Following their work, we develop sentiment-based hypotheses based on the sentiment intensity of social media posts or the sentiment polarity of social media posts.

Social media sentiment intensity indicates how strong the sentiment (regardless of whether or not this sentiment is positive or negative) reflected in social media posts can be. Previous literature shows that social media posts that carry a very intense sentiment (extremely positive or negative) tend to spread faster (Stieglitz & Dang-Xuan, 2013). Sentiment intensity of social media posts at aggregate level suggests high attention. Ren and Nickerson (2019) examined the sentiment intensity of online reviews (measured by the emotionally charged words in review text) and concluded that the sentiment intensity of online reviews influences product sales. Therefore, we argue that when the sentiment of social media discussions about a topic is stronger, such a topic attracts and reflects more attention and that can trigger people to further seek professionally reported information on this topic. We argue that when a popular topic receives more intense sentiment (that shows a very strong emotion regardless of whether or not this sentiment is positive or negative) on social media platforms, this strengthens the association between social media volume and traditional media viewership. In other words, with more attention amplified by the sentiment intensity of social media posts added on top of the attention level measured by social media post volume, the positive relationship between social media post volume and the news article viewership is stronger.

H2. The positive association between social media volume about a stock and news article viewership on the same stock is stronger when the sentiment of the relevant social media posts is more intense.

2.4.2. Social media post sentiment

Social media sentiment indicates the sentiment (positive or negative) reflected in social media posts. Researchers studied the raw value of sentiment of user-generated content (e.g., positive proportion of all ratings) and how it influences people's decisions (Chevalier & Mayzlin, 2006; Dellarocas et al., 2007; Ren & Nickerson, 2019; Ren et al., 2018). A widely accepted behavioural theory argues negativity bias: negative information attracts more attention than positive information because people's brains are wired to pay attention to warnings (Jha & Shah, 2019; Kahneman et al., 1991; Rozin & Royzman, 2001). That is, social media posts with negative sentiment in the stock market imply warnings and thus suggest high attention. The stock market could exhibit a negativity bias.

However, another stream of literature argues positivity bias. Loewenstein (2006) argued that information causes pain or pleasure to information users, so individuals are more inclined to read information that causes pleasure. Specific to the stock market, positive information typically brings pleasure. That is, individual investors benefit from an increase in stock returns and suffer from a decrease in stock returns because most individual investors do not short sell stocks (Barber & Odean, 2008). This is known as the "ostrich effect", i.e., investors avoid reading negative information (Galai & Sade, 2006; Karlsson et al., 2009). Karlsson et al. (2009) and Sicherman et al. (2016) provided strong evidence for the ostrich effect. According to them, positive social media posts attract more attention.

Moreover, the recipients of positive social media posts are broader than those of negative social media posts. All investors can buy stocks, but only shareholders can sell stocks – positive information tends to attract the attention of all investors; and negative information is attractive only to investors who hold relevant stocks (Barber & Odean, 2008; Engelberg et al., 2011). That is, a positive social media post is attractive to more investors than a negative social media post. The stock market could exhibit a positivity bias.

Since there is no consensus in academia on whether there is a positivity bias or a negativity bias in the stock market, we propose competing hypotheses regarding information sentiment on social media. In other words, we hypothesise that when a popular topic receives negative sentiment on social media (when a popular topic is negatively received) or a popular topic receives positive sentiment on social media (when a popular topic is positively received), this strengthens the association between social media volume and traditional media viewership:

H3a. The positive association between social media volume about a stock and news article viewership on the same stock is stronger when the sentiment of relevant social media posts is negative.

H3b. The positive association between social media volume about a stock and news article viewership on the same stock is stronger when the sentiment of relevant social media posts is positive.

2.4.3. Social media post source verifiability

After Twitter introduced the "blue tick" to indicate that they had verified a user's identity and credentials, other social media platforms started doing the same. Source verifiability of social media posts indicates the percentage of verified social media users discussing a particular topic. Verified users disclose their professions and are more responsible for what they say online (Shu et al., 2019). And many of them are professionals in financial markets. Moreover, this group of verified users is often the focus of social networks in social media and tends to have more followers. When some influencers (e.g., the CEO of a company or a famous stock analyst) discuss a topic, that topic is worth paying attention to. Therefore, the percentage of verified users discussing a topic indicates a high level of attention that people should pay to that topic. If a popular topic on social media platforms comes from verified accounts, the association between social media volume and traditional media viewership will be stronger. Thus, we propose:

H4. The positive association between social media volume about a stock and news article viewership on the same stock is stronger when more verified social media users have discussed that stock.

3. Data

Our datasets come from Sina Finance[4] and Sina Weibo[5]. Sina Finance is a leading online financial news platform in China (comparable to Yahoo! Finance). Almost all publicly available stock market news in China is displayed on this platform. Sina Weibo is one of the most influential social media platforms in China (Ge et al., 2017), analogous to Twitter in the US. According to Sina's annual report, as of December 2019, Sina Weibo had 516 million monthly active users (about 94% of these users accessed Weibo at least once a month from mobile devices) and an average of 222 million daily active users. It was one of the largest social media platforms in the world in 2019.

We were careful to avoid selection bias. We found no evidence that Sina Finance and Sina Weibo are interdependent. They are separate platforms, and both are listed on the US stock exchange. Weibo users can post their information or forward information from any news source, including Sina Finance. Our original news database contained all news articles from Sina Finance for the available two-year period (2013 and 2014) – approximately 1.4 million articles. Sina Finance generates some news articles about the stock market in general, by contrast to articles about individual stocks; these general articles may include many tickers. We removed such articles from our dataset during the data cleansing process.

Sina extracts weibos that mention Chinese stocks by using a combination of stock tickers and *Jiancheng*, the short name in Chinese, to identify a stock. For example, "$PetroChina sh601857 USD" is used to identify PetroChina, the largest listed company in the Chinese market. "601,857" in this case is a ticker that typically has no meaning in a non-stock environment. This unique feature allows Sina Weibo to perfectly match weibos to stocks. Our original dataset contained all stock-related original weibos and weibo reposts (about 50 million records) for the time period that matches the news database. For the same reason, we decided to examine the social media posts that mention only one stock.

Sina provided us with the sentiment of each weibo (e.g., positive, negative, and neutral). We checked the sentiment measurement using a third-party software package – BosonNLP. BosonNLP is a third party commercial natural language processing (NLP) platform. It uses a sentiment dictionary to determine the sentiment of texts. Zheng et al. (2019) provide more details about BosonNLP. They use BosonNLP to test the validity of Sina Weibo's sentiment, which they use to measure people's happiness. The analysis showed 83% agreement between Sina's sentiment classification and our results. We collected the stock-related data from Resset's database. Resset is an academic economic database that is widely used in the literature. It is similar to CRSP but focuses on the Chinese market. This dataset is a commonly used academic database on the Chinese market (Dong & Gil-Bazo, 2020; Ren et al., 2021).

We combined the social media data with the Sina news data and the stock data. Stock and day were the matching variables. In the dataset for analysis, we only included the aggregated data based on stock and day. After data aggregation, our dataset included 2,670 Chinese stocks. We used Stata (version 14) to perform our analysis.

3.1. Variable definitions

3.1.1. Dependent variable: news article viewership

Since the dataset is panel data, we aggregated the views of all news articles relevant to the stock s on day t, the day these news articles were first published. Because the number of views is skewed (some news articles receive a large number of views, while others attract only a few), we operationalised the news view variable as the natural logarithm of the number of views (page views or PV) plus one for stock s on day t. That is,

$$Viewership_{s,t} = \ln\left(1 + PV_{s,t}\right)$$

where $Viewership_{s,t}$ is the news article viewership on stock s on day t. $PV_{s,t}$ is the sum of the number of views on all relevant news articles about stock s on day t.[6]

Throughout the paper, t is the natural day when a news article is first published, and the time difference between t-1 and t is one day.

3.1.2. Independent variable: social media volume

Similarly, we aggregated the volume of social media posts relevant to the stock s on day t to measure social media volume. We logarithmized the variable as the natural logarithm of the volume of all social media posts related to stock s on day t plus one. That is,

$$VolWeibo_{s,t} = \ln(1 + m_{s,t})$$

where $VolWeibo_{s,t}$ is the social media volume on stock s on day t. $m_{s,t}$ is the number of all social media posts about stock s on day t.

3.1.3. Moderator: social media sentiment intensity

Sina uses its proprietary sentiment dictionary to measure the sentiment of a weibo. Sina assigns a sentiment value to each sentiment word and then sums all sentiment values in each social media post (in each weibo) to get the sentiment value – positive, neutral, and negative (coded as 1, 0, and −1). We do not have access to the texts of the weibos. As we explained in Section 3.1, after verifying Sina's sentiment measure, we used the sentiment score that Sina assigned to each weibo to calculate social media sentiment-related variables. We defined social media sentiment intensity as the natural logarithm of one plus the ratio of one plus the absolute value of the difference between the number of positive weibos and the number of negative weibos over one plus the number of all weibos about stock s on day t. This is,

$$SentIntWeibo_{s,t} = \ln\left(1 + \frac{1 + |m_{p,s,t} - m_{n,s,t}|}{1 + m_{s,t}}\right)$$

where $SentIntWeibo_{s,t}$ is the social media post sentiment intensity for stock s on day t; $m_{p,s,t}$ ($m_{n,s,t}$) is the number of positive (negative) weibos about stock s on day t; and $m_{s,t}$ is the number of weibos about stock s on day t.

3.1.4. Moderator: social media sentiment positivity

We calculated social media sentiment in the same way as Antweiler and Frank (2004):

$$SentWeibo_{s,t} = ln\left(\frac{1 + m_{p,s,t}}{1 + m_{n,s,t}}\right)$$

where $SentWeibo_{s,t}$ is the proxy for social media sentiment for stock s on day t, and $m_{p,s,t}$ ($m_{n,s,t}$) is the number of social media posts with positive (negative) sentiment for stock s on day t. The higher the value of the variable, the more positive the social media sentiment.

3.1.5. Moderator: social media source verifiability

Our dataset provides a valuable way to measure the verifiability of sources. In particular, Weibo users can voluntarily disclose their professional identities (e.g., financial analyst, mutual fund manager). As a result, Weibo labels these users as verified users (V-users). V-users must be accountable for the content of their weibo and can be held accountable by losing their verified status. Following this logic, we define source verifiability for stock s on day t as the proportion of weibos posted by V-users compared to weibos posted by non-V-users for stock s on day t. Specifically,

$$VeriWeibo_{s,t} = \ln\left(\frac{1 + m_{v,s,t}}{1 + m_{nv,s,t}}\right)$$

where $VeriWeibo_{s,t}$ is the proxy for the verifiability of social media sources for stock s on day t. $m_{v,s,t}$ ($m_{nv,s,t}$) is the number of weibos posted by V-users (non-V-users) for stock s on day t.

3.1.6. Control variables

We have controlled for the inherent properties of the topics that news articles report on. In the stock market, these fundamental properties are stock return and stock size. We used raw returns as a proxy for daily stock returns and decoded them as $Return_{s,t}$. We also controlled for stock size or market capitalisation, which is defined as the closing price multiplied by the number of shares. Typically, news articles about large companies would receive more attention and higher viewership. Because of the skewed distribution, we log-transformed this variable and decoded it as $Size_{s,t}$.

Another control variable was the volume of news articles about stock s at time t, which affects viewership. Consistent with Engelberg et al. (2011), news coverage indicates the extent to which a stock attracts attention. Therefore, it is likely that this coverage increases viewership. Given the skewed distribution, we log-transformed this variable and decoded it as $VolNews_{s,t}$.

Another important control variable is the viewership of relevant news articles first published at time *t-1*. This raises the possibility of an autocorrelation problem, since social media volume is a product of the previous day's news viewership. Thus, the effect of social media volume at time *t-1* on traditional media viewership that we observe at time t is, in fact, the effect of traditional media viewership at time *t-1* on viewership at time t. To avoid this autocorrelation problem, we controlled for $Viewership_{s,t-1}$. Note, however, that the influence of autocorrelation is inherently smaller in the stock market than in other contexts (e.g., in a political environment). This smaller influence is due to the fact that information is quickly reflected in the stock price. Therefore, it is not sufficient motivation for traditional media to report the same story the next day.

Given the structure of the panel data, we controlled for stock-fixed effects and day-fixed effects related to time-varying factors such as stock market

Table 1. Descriptions of variables.

Acronym	Variable	Measure
Viewership	News Article Viewership	The natural logarithm of one plus the number of views (page views, or PV) on all relevant news articles about stock *s* on day *t*.
VolWeibo	Social Media Volume	The natural logarithm of one plus the number of all weibos about stock *s* at day *t*.
SentIntWeibo	Social Media Sentiment Intensity	The natural logarithm of one plus the ratio of one plus the absolute value of the difference between the number of positive weibos and the number of negative weibos over one plus the number of all weibos about stock s on day *t*.
SentWeibo	Social Media Sentiment Positivity	The natural logarithm of one plus the number of positive weibos over one plus the number of negative weibos about stock *s* on day *t*. That is, the higher the number, the more positive the sentiment.
VeriWeibo	Social Media Information Verifiability	The natural logarithm of one plus the proportion of weibos published by verified users over weibos published by nonverified users on stock *s* on day *t*.
Return	Daily Stock Return	The daily raw return of stock *s* on day *t*.
Size	Stock Size	The natural logarithm of one plus the market capitalisation of the company stock s on day *t*.
VolNews	News Article Volume	The natural logarithm of one plus the number of all news articles about stock *s* on day *t*.

Table 2. Summary statistics (in their original format before mean-centring).

Variable Acronym	Observations	Mean	Std. Dev.	Min	Max
Viewership	139,934	4.47	1.95	0.69	12.24
VolWeibo	139,934	2.94	1.71	0.00	11.85
SentIntWeibo	139,934	0.42	0.20	0.00	0.69
SentWeibo	139,934	1.32	1.37	−6.74	9.22
VeriWeibo	139,934	0.41	0.30	0.00	4.37
Return	139,934	0.00	0.03	−0.10	0.17
Size	139,934	3.17	0.05	3.06	3.37
VolNews	139,934	0.99	0.45	0.69	5.32

performance, day-of-week effects, and weather. Finally, we mean-centred all variables. For our analysis, we discarded observations in which stock *i* has no news on day *t* – stocks do not have news every day. The distribution is consistent with previous literature (Fang & Peress, 2009). Finally, we have 139,934 stock-day observations. Tables 1, 2 , 3 , and 4 contain the descriptions, summary statistics, and correlation statistics for all variables before mean centring.

4. Methodology and results

4.1. Main analysis

Based on our panel data structure, we ran fixed-effects models as follows.

Model 1 (with control variables only):

$$\begin{aligned}Viewership_{s,t} = \alpha_s + \alpha_t + Return_{s,t-1} + Return_{s,t} \\ + Size_{s,t-1} + Size_{s,t} + VolNews_{s,t} \\ + Viewership_{s,t-1} + \varepsilon_{s,t}\end{aligned}$$

Model 2 (H1, baseline):

$$\begin{aligned}Viewership_{s,t} = \alpha_s + \alpha_t + \beta_1 VolWeibo_{s,t-1} \\ + Return_{s,t-1} + Return_{s,t} + Size_{s,t-1} \\ + Size_{s,t} + VolNews_{s,t} \\ + Viewership_{s,t-1} + \varepsilon_{s,t}\end{aligned}$$

Model 3 (H2, H3, and H4):

$$\begin{aligned}Viewership_{s,t} = \alpha_s + \alpha_t + \beta_1 VolWeibo_{s,t-1} + \beta_2 SentIntWeibo_{s,t-1} + \beta_3 SentIntWeibo_{s,t-1} \\ \times VolWeibo_{s,t-1} + \beta_4 SentWeibo_{s,t-1} + \beta_5 SentWeibo_{s,t-1} \times VolWeibo_{s,t-1} \\ + \beta_6 VeriWeibo_{s,t-1} + \beta_7 VeriWeibo_{s,t-1} \times VolWeibo_{s,t-1} \\ + Return_{s,t-1} + Return_{s,t} + Size_{s,t-1} + Size_{s,t} + VolNews_{s,t} + Viewership_{s,t-1} + \varepsilon_{s,t}\end{aligned}$$

where α_s and α_t are stock and time fixed effects, $\varepsilon_{s,t}$ is the error term. All other variables are defined in Table 1.

Table 4 shows the results. Model 1 includes only the control variables, i.e., stock returns at time *t-1* and at *t*, stock size at time *t-1* and *t*, news coverage at time *t*, and news viewership at time *t-1*. All variables, except stock size at time *t*, positively affect traditional media viewership at time *t*.

Model 2 serves as our baseline test. It includes the independent variable, which is social media volume, and control variables. The results show that social media volume is associated with traditional media viewership on thenext day (0.14, $p < 0.01$), with the effects of the control variables being the same as in Model 1. H1 was supported.

Model 3 includes the moderating effects between social media volume and one of the moderators described above. The results show that the effects of the control variables and the independent variable, social media volume, remain the same. Moreover, the three interaction terms between social media volume and social media sentiment intensity, between social media volume and social media sentiment positivity, and between social media volume and social media source verifiability are all positive and significant (0.06, $p < 0.01$; 0.004, $p < 0.1$; 0.08, $p < 0.01$). This suggests that H2 to H4 were supported.

Table 3. Correlation statistics (in their original format before mean-centring).

	$Viewership_t$	$VolWeibo_{t-1}$	$SentIntWeibo_{t-1}$	$SentWeibo_{t-1}$	$VeriWeibo_{t-1}$	$Return_{t-1}$	$Return_t$	$Size_{t-1}$	$Size_t$	$VolNews_t$	$Viewership_{t-1}$
$Viewership_t$	1										
$VolWeibo_{t-1}$	0.24***	1									
$SentIntWeibo_{t-1}$	−0.11***	−0.40***	1								
$SentWeibo_{t-1}$	0.06***	0.50***	0.22***	1							
$VeriWeibo_{t-1}$	−0.15***	−0.48***	0.17***	−0.24***	1						
$Return_{t-1}$	0.05***	0.16***	0.12***	0.27***	−0.08***	1					
$Return_t$	0.06***	0.03***	0.03***	0.07***	−0.03***	0.11***	1				
$Size_{t-1}$	0.34***	0.35***	−0.18***	0.06***	−0.20***	−0.01***	−0.05***	1			
$Size_t$	0.35***	0.33***	−0.18***	0.07***	−0.20***	−0.01***	−0.03***	0.99***	1		
$VolNews_t$	0.56***	0.22***	−0.11***	0.02***	−0.13***	0.00	0.02***	0.34***	0.35***	1	
$Viewership_{t-1}$	0.31***	0.36***	−0.15***	0.09***	−0.16***	0.05***	−0.00	0.39***	0.33***	0.90***	1

Note: *** $p < 0.01$.

Table 4. Results of the fixed-effects models.

	Model 1	Model 2	Model 3
Estimation Method	Fixed-Effects Models with Day Fixed Effects and Stock Fixed Effects		
Dependent Variable	*$Viewership_{s,t}$*, defined as the natural logarithm of one plus all the clicks on stock *s* at *t*		
$Return_{s,t-1}$	2.54***	1.23***	1.33***
	(0.16)	(0.16)	(0.17)
$Return_{s,t}$	5.82***	5.60***	5.61***
	(0.37)	(0.37)	(0.37)
$Size_{s,t-1}$	38.01***	32.74***	32.07***
	(8.08)	(8.05)	(8.05)
$Size_{s,t}$	−24.41***	−22.67***	−22.10***
	(8.07)	(8.05)	(8.04)
$VolNews_{s,t}$	0.22***	0.18***	0.18***
	(0.02)	(0.02)	(0.02)
$Viewership_{s,t-1}$	0.06***	0.05***	0.05***
	(0.00)	(0.00)	(0.00)
$VolWeibo_{s,t-1}$		0.14***	0.19***
		(0.00)	(0.01)
$SentIntWeibo_{s,t-1}$			0.32***
			(0.04)
$SentIntWeibo_{s,t-1}$ * $VolWeibo_{s,t-1}$			0.06***
			(0.01)
$SentWeibo_{s,t-1}$			−0.08***
			(0.01)
$SentWeibo_{s,t-1}$ * $VolWeibo_{s,t-1}$			0.004*
			(0.00)
$VeriWeibo_{s,t-1}$			−0.10***
			(0.02)
$VeriWeibo_{s,t-1}$ * $VolWeibo_{s,t-1}$			0.08***
			(0.01)
Fixed Stock Effects	Yes	Yes	Yes
Fixed Day Effects	Yes	Yes	Yes
Num of Obs	139,934	139,934	139,934
Adjusted R squared	0.3103	0.3152	0.3163

Note: Coefficient (standard error); * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

4.2. Causality tests

The initial tests show strong evidence that the social media volume for stock s at time *t-1* is related to the news viewership about stock *s* at time *t*. In our stock market setting, as we discussed in the introduction, information is less likely to appear first on social media – our paper suffers less from endogeneity issues. However, we acknowledge that there are still some persistent possibilities of endogeneity problems that prevent us from arguing a causal relationship between social media volume and news article viewership.

The endogeneity issues result from two aspects: First, traditional media repeats information. That is, a piece of information appears in traditional media at time *t-2*, social media discusses the same information at time *t-1* and traditional media reports the outdated information again at time *t* (Tetlock, 2011). Previous studies argued that social media is more likely to repeat information in traditional media and social media users respond to the stale information in social media (Jia et al., 2020; Jiao et al., 2020). In this case, we would still have an endogeneity problem that the association between news viewership at *t* and social media characteristics at *t-1* is driven by the news viewership at *t-2*. To rule out this possibility, following Ren et al. (2021), we conducted a robustness test using observations without news articles from *t-7* to *t-1* (see column 1 of Table 5: 0.09, $p < 0.01$). The idea is that listed companies are required by the regulator to disclose any fundamental information through traditional media – if there is no news report in the past week, we may observe less stale information in social media. Another way to interpret this test is that when there is no fundamental information during the past week, social media is less likely to play the role of an information diffusion channel.

Second, our analyses still suffer from the endogeneity that our empirical results are driven by unobservable variables (e.g., past and current stock returns). In all our regressions, we controlled for the stock and day fixed effects, i.e., all unobservable stock-specific and day-specific variables are controlled for. To control for other unobservable variables, we adopted the approach used in Garcia (2013) and Siganos et al. (2014), which considers only a subsample on Mondays. The idea is that on weekends the stock markets are closed; no news articles are published (at least in the stock market). Column 2 of Table 5 shows that social media volume for stocks not covered by traditional media can still explain the viewership of news articles covering those stocks the next day (0.16, $p < 0.01$). In addition, we added a new test in column 3. Column 3 refers to a scenario where there was no trading for stock *s* at *t*. The idea of this scenario is to examine

Table 5. Results of the Fixed-Effects models.

	Column 1 (With no prior news coverage at t-1 through t-7)	Column 2 (With t-1 as Sundays and t as Mondays)	Column 3 (With no trading for stock s at t)
Estimation Method	Fixed-Effects Models with Day Fixed Effects and Stock Fixed Effects		
Dependent Variable	$Viewership_{s,t}$, defined as the natural logarithm of one plus all the clicks on stock s at t		
$Return_{s,t-1}$	1.95***		0.44
	(0.30)		(0.39)
$Return_{s,t}$	6.29***		
	(0.47)		
$Size_{s,t-1}$	25.12***		7.78***
	(9.54)		(1.32)
$Size_{s,t}$	−13.59		
	(9.54)		
$VolNews_{s,t}$		−0.11**	2.23***
		(0.05)	(0.04)
$Viewership_{s,t-1}$		0.08***	0.03***
		(0.01)	(0.00)
$VolWeibo_{s,t-1}$	0.09***	0.16***	0.09***
	(0.01)	(0.01)	(0.01)
Fixed Stock Effects	Yes	Yes	Yes
Fixed Day Effects	Yes	Yes	Yes
Num of Obs	42,100	39,139	20,177
Adjusted R squared	0.2194	0.2263	0.3874

Note: Coefficient (standard error); * p < 0.1; ** p < 0.05; *** p < 0.01.

whether our hypothesis stands in the absence of stock return at *t*. The result consistently shows that social media volume has a positively association with traditional media news viewership on the next day when the involved stock does not have trading at all. As such, we have minimised the following influence of unobservable variables, which is that social media affects traditional news viewership through the impact of stocks on news viewership.

Moreover, given the bidirectional relationship between social media and traditional media and their autocorrelated relationship, we conducted a Granger causality test for social media volume and news article viewership in traditional media (Love & Zicchino, 2006). This test is a well-accepted approach in the IS field to test for causality (see discussions in Deng et al. (2018) and Dewan and Ramaprasad (2014)).

We conducted the Harris-Tzavalis unit root tests for the variables involved (Harris & Tzavalis, 1999), and the results supported the stability of the estimates. Based on the selection criteria of Andrews and Lu (2001), we selected a third-order panel VAR for the models with the control variables because it has the smallest MBIC, MAIC, and MQIC (Love & Zicchino, 2006). We used three days as the optimal time lag for the Granger causality test. The Granger causality tests (see, Table 6) show that social media volume and traditional media news article viewership Granger-cause each other (χ^2 = 23,113.771, p < 0.001, χ^2 = 3295.107, p < 0.001), with a larger effect for social media volume Granger-causing traditional media news article viewership. This confirms the effect of social media on the viewership of news in traditional media.

Table 6. Granger causality test results.

Equation	Excluded	χ^2	df	Prob > χ^2
Viewership	VolWeibo	23,113.771	3	***
	All	23,113.771	3	***
VolWeibo	Viewership	3295.107	3	***
	All	3295.107	3	***

Note: The optimal time lag is 3. *** p < 0.01.

Finally, Sina provided us with another dataset. We have daily data on the number of unique visitors (UV) who visited Sina Finance news from Weibo from April 2018 to July 2018. This presents a unique opportunity because Sina is the only major company that provides social media and traditional media services. We found that news viewing in traditional media through posts on social media platforms ranges from 8% to 40%. The percentage is much higher (almost double) on weekends or holidays. This is direct evidence that Weibo users visit Sina Finance to read news articles about their activities on Weibo. Thus, this strongly supports our discovered impact of social media information on traditional media news viewership.

4.3. Robustness Checks

In the primary analysis above, we log-transformed the sum of the viewership of all relevant news articles about a stock to calculate our dependent variable. We also controlled for the number of relevant news articles. In the robustness checks section, we performed four tests. First, we log-transformed the average viewership of all relevant news articles about a stock, used $AveViewership_{s,t}$ as the dependent variable, and used $AveViewership_{s,t-1}$ as the control variable. The results remained the same (see the first column in Table 7). Second, we controlled for industry fixed effects instead of stock fixed effects and reran the

Table 7. Results of robustness checks.

	Column 1 (with $AveViewership_{s,t}$ as the dependent variable)	Column 2 (with fixed industry effects instead of fixed stock effects)	Column 3 (GLS model)	Column 4 (with standard errors clustered on stock and date)
$Return_{s,t-1}$	1.29***	0.57***	1.33***	1.23***
	(0.15)	(0.17)	(0.13)	(0.21)
$Return_{s,t}$	4.83***	5.55***	5.45***	5.60***
	(0.33)	(0.39)	(0.35)	(0.41)
$Size_{s,t-1}$	28.31***	31.92***	36.62***	32.74***
	(7.26)	(8.48)	(7.71)	(8.45)
$Size_{s,t}$	−19.50***	−24.51***	−27.27***	−22.67***
	(7.25)	(8.48)	(7.71)	(8.29)
$VolNews_{s,t}$	0.07***	0.42***	0.24***	0.18***
	(0.01)	(0.02)	(0.02)	(0.03)
$AveViewership_{s,t-1}$	0.04***			
	(0.00)			
$Viewership_{s,t-1}$		0.06***	0.08***	0.05***
		(0.00)	(0.00)	(0.01)
$VolWeibo_{s,t-1}$	0.12***	0.17***	0.13***	0.14***
	(0.00)	(0.00)	(0.00)	(0.01)
Fixed Stock Effects	Yes	No	No	Yes
Fixed Industry Effects	No	Yes	No	No
Fixed Day Effects	Yes	Yes	No	Yes
Num of Obs	139,934	139,934	139,934	139,934
Adjusted/Pesudo R squared	0.2352	0.2211	0.2052	0.3152

Note: Coefficient (standard error); * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

main regression. The second column in Table 7 shows the result, which is consistent with that in Table 4. We also ran the analyses for the full model. The results are consistent and upon request.

Another problem is the heteroscedasticity. We followed two steps to mitigate this concern. In the third robustness test, we performed the random effects regression using GLS estimation. The results reported in column 3 of Table 7 are consistent with those of the main analysis. To further mitigate the problem of heteroscedasticity, in the fourth robustness test we followed Petersen (2009) and Gow et al. (2010) and clustered the standard errors to control for heteroscedasticity. These authors argue that regressions with two-way standard error clustering provide a more accurate result. So, we added the clusters for stock and date to the fixed effects model. The results reported in column 4 of Table 7 are consistent with those of the main analyses.

We also reran the models with different time intervals that are 2 days, 3 days, 4 days, 5 days, 6 days, and 7 days. Table A2 in the Appendix shows the results. With the different time intervals, our findings still hold – social media volume of prior days positively affect traditional media news viewership.

5. Discussion

5.1. Summary of the findings and implications for research

Our study suggests that social media influences the viewership of traditional media. More specifically, the higher the volume that social media platforms generate about a news topic, the more viewers that topic attracts. And this relationship is strengthened when social media posts on this topic are more intense or positive, or when more sources of those social media posts on this topic are verified. Table 8 lists the findings.

The most important contribution that our paper makes is to treat social media as an attention driver. Our findings suggest that social media attracts and reflects attention to a topic and such attention can translate to higher viewership of news articles on the same topic. Essentially our paper proposes a different

Table 8. Summary of findings.

Hypothesis	Finding
H1. The volume of social media posts about a stock at time t-1 is positively associated with the viewership of news articles on the same stock at time t.	Supported
H2. The positive association between social media volume about a stock and news article viewership on the same stock is stronger when the sentiment of relevant social media posts is more intense.	Supported
H3a. The positive association between social media volume about a stock and news article viewership on the same stock is stronger when the sentiment of relevant social media posts is negative.	Rejected
H3b. The positive association between social media volume about a stock and news article viewership on the same stock is stronger when the sentiment of relevant social media posts is positive.	Supported
H4. The positive association between social media volume about a stock and news article viewership on the same stock is stronger when more verified social media users have discussed that stock.	Supported

working mechanism for why social media complements traditional media for viewership. Two recent papers (Bar-Gill et al., 2020; Sismeiro & Mahmood, 2018) treat social media as information channels that share news article links and provide evidence to show that social networking sites (Facebook) complement traditional media for viewership. Our paper together with these two papers all collectively challenge the long-held assumption many regulators and scholars hold that social and traditional media complete for viewership (Miranda et al., 2016; Sismeiro & Mahmood, 2018).

Treating social media as an attention driver, our findings are useful in explaining many phenomena documented in the literature. For example, Clarke et al. (2020) showed that fake news spreads faster than legitimate news. This is plausible because fake news carries a stronger sentiment and attracts more attention. Castillo et al. (2021) showed that social media-driven customer engagement is positively associated with movie performance. This can be interpreted to mean that social media reminds customers of the movie's existence and thus includes the movie in customers' choice set.

Moreover, our work contributes to the literature on the predictive or explanatory role of social media (Banerjee et al., 2017; Mai et al., 2018; Yin et al., 2016) in the stock market. Specifically for the financial market, Deng et al. (2018) showed that social media sentiment significantly granger-causes stock returns, and Mai et al. (2018) demonstrated that social media significantly affects bitcoin value. Our paper, on the other hand, extends the explanatory role of social media in relation to the media industry in the stock market and is among the first to study how social media influences the audience of traditional media in the stock market.

In addition, our results indirectly contribute to research on media bias. Much work on media bias explicitly assumes that the current primary purpose of traditional media is to attract readers and that news bias serves this purpose (Gentzkow & Shapiro, 2010; Puglisi & Snyder, 2015). Although we did not address demand-driven media bias per se, our results show that audience attention, as reflected by social media platforms, influences which news stories are ultimately seen in traditional media.

5.2. Implications for practice

Our findings have important practical implications. First, our results have strong implications for news recommendation systems. In addition to recommending news articles that match each reader's tastes, these systems can also constantly monitor the number of social media posts to suggest news articles that are of interest to all readers to ensure (1) a high audience for news articles and, accordingly, (2) increased usage of these systems.

In this sense, our results also have practical implications for traditional media creators. Viewership is a valuable resource for traditional media creators because it is associated with influence and advertising revenue (Gentzkow & Shapiro, 2010; Puglisi & Snyder, 2015). Our findings suggest that in order to increase viewership of news articles, traditional media creators may intentionally trigger social media discussions about the relevant news topics with more intense or positive sentiment or encourage verified social media account holders to discuss the relevant news topics.

Our results also serve as a warning to policymakers and regulators who currently treat all media as competing participants in a zero-sum game. Our results suggest that social media is not currently stealing the show from traditional media audiences. Arbitrarily blocking or reducing connectivity between these media may hinder the market recovery of the entire media industry. This obstacle can lead to significant declines in viewership for all news media involved. After a law was passed in Spain that forced all news users to pay to cite news links, Spanish traditional media lost 10% to 20% of viewers, resulting in annual revenues of 9 million to 18 million euros (Carleton Athey et al., 2017). This policy failure is consistent with our descriptive analysis. In our case, social media leads to additional viewership of traditional media – 8% to 40% of news viewership of Sina Finance came from Weibo activities.

5.3. Limitations and future research

When it comes to evaluating the contributions of this study, it is important to examine the limitations that also provide opportunities for future research. First, we used stocks as a subject to associate social media and traditional media. This assumes that users of social media platforms and news readers are the same group of people (e.g., stock investors) or have the same distribution of attention. Given the size of the dataset, our assumption is reasonable. Nonetheless, researchers could replicate this study in a laboratory setting where participants can indicate how much they want to talk about a news topic and how much they tend to read relevant news articles. However, this experimental approach is not without problems (e.g., it may suffer from self-report bias and small sample size).

Second, although Sina provided a rich dataset and allowed us to examine factors that influence the use of traditional media, we did not have access to the actual texts of posts on social media platforms. This was done to protect the privacy of social media platform users. Therefore, we could not fully understand the more detailed characteristics of these social media platform posts to further enrich our results. We believe that our results have already opened the door to studies on the possibility of using social media to explain the audience of traditional media.

Third, we mainly examined the aggregate attributes of social media platform posts (volume, sentiment, and sources) that influence traditional media viewership. However, social media also has other attributes that have the potential to influence traditional media viewership. One of these, for example, is visibility – whether or not these posts are included in the category of "hot" weibos. This labelling feature on some social media platforms may influence how users of social media platforms interact with social media posts and further influence their interest in the topics being discussed. We advocate for future research that empirically examines how the visibility of social media platform posts influences the explanatory power of social media in determining the audience of traditional media news.

Finally, we examined the explanatory power of social media for the stock market. We believe our findings apply to other settings as well. For example, in the entertainment industry, social media platforms show how influential celebrities are. The social media influence of celebrities can also affect the viewership of relevant news articles that report extensively on those celebrities. For example, fans of Justin Bieber interact through social media platforms and want to read more information about Justin Bieber from traditional media coverage. We call for replication of our research in other settings.

6. Conclusion

Social media is significantly transforming the news industry. Viewership is valuable to traditional media because it translates into advertising and revenue. This study is one of the first attempts to examine how social media at time *t-1* affects traditional media's viewership at time *t*. We argue that social media acts as an attention driver. To the best of our knowledge, we are the first in the literature to explicitly discuss this mechanism.

Using robust data from Sina Weibo and Sina Finance, we find that the volume of social media posts about a stock affects traditional media news viewership for the same stock the next day. Moreover, this effect is amplified when these posts on social media platforms are more intense or positive, or when the sources of these social media posts are more verifiable. Using multiple causality tests, we confirmed the presumed explanatory power of social media. Our research opens up possibilities for a new stream of literature attempting to explain traditional media's viewership, and also suggests that social media and traditional media may not be as competitive as many regulators assume – social media does not steal viewership from traditional media; instead, it draws attention to traditional media and increases news viewership. We hope that this work will inspire future attempts at a more elaborate and comprehensive understanding of such capability-building phenomena.

Notes

1. We define traditional media as the digitalised print media (such as news articles).
2. https://www.politico.eu/article/europe-us-digital-tax-trade-war/
3. Given the nature of traditional media – they typically only update news at a daily frequency, t represents natural day.
4. https://finance.sina.com.cn/
5. https://weibo.com/
6. We used one plus transformation to avoid the impact of zero values.

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Appendix

Table A1. Social media post on #TheFormerChairmanofGuanshengyuanKilledByAMonkeyWithStone.

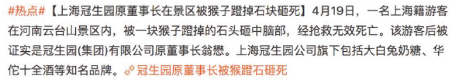
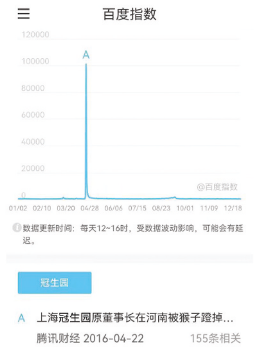
Description	Screenshot
Weibo Post on #TheFormerChairmanofGuanshengyuanKilledByAMonkeyWithStone: "on April 19th, a tourist from Shanghai in the sightseeing area of Henan Yutai Mountain was hit by a monkey sitting in a tree and accidentally dropping a stone at him and passed away soon after	
Baidu Search Index showing that there is a pike in search volume for news articles related to Guanshengyuan	

Table A2. Results of the fixed-effects models with different time intervals.

	Column 1 (with i as the time interval of 2 days)	*Column 2 (with i as the time interval of 3 days)*	*Column 3 (with i as the time interval of 4 days)*	*Column 4 (with i as the time interval of 5 days)*	*Column 5 (with i as the time interval of 6 days)*	*Column 6 (with i as the time interval of 7 days)*
Estimation Method	Fixed-Effects Models with Day Fixed Effects and Stock Fixed Effects					
Dependent Variable	*$Viewership_{s,t}$, defined as the natural logarithm of one plus all the clicks on stock s at t*					
$Return_{s,t-1}$	2.16***	2.31***	2.34***	2.35***	2.36***	2.38***
	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
$Return_{s,t}$	4.50***	4.56***	4.56***	4.55***	4.58***	4.59***
	(0.33)	(0.33)	(0.33)	(0.33)	(0.33)	(0.33)
$Size_{s,t-1}$	27.04***	28.21***	28.37***	28.34***	28.52***	28.44***
	(7.19)	(7.19)	(7.19)	(7.19)	(7.19)	(7.19)
$Size_{s,t}$	−18.34**	−18.98***	−18.86***	−18.63***	−18.92***	−18.90***
	(7.18)	(7.18)	(7.19)	(7.18)	(7.19)	(7.19)
$VolNews_{s,t}$	2.27***	2.27***	2.27***	2.27***	2.27***	2.27***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Viewership_{s,t-1}$	0.04***	0.04***	0.05***	0.05***	0.05***	0.05***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$VolWeibo_{s,t-i}$	0.08***	0.06***	0.05***	0.04***	0.05***	0.05***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Fixed Stock Effects	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Day Effects	Yes	Yes	Yes	Yes	Yes	Yes
Num of Obs	139,934	139,934	139,934	139,934	139,934	139,934
Adjusted R squared	0.4546	0.4538	0.4535	0.4648	0.4534	0.4534

Note: Coefficient (standard error); * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.