Be Careful What You Read – Evidence of Demand-driven Media Bias

Completed Research

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Abstract

This paper provides empirical evidence for demand-driven media bias. Social media allows mass media professionals to first discover what readers want to read and then please these readers with news articles tailored to reader's desires. To study this phenomenon, a large Chinese dataset involving 4.27 million pieces of stock news and with 43.17 million stock-related microblogs that span two years was examined. Specifically, social media facilitates the generation of homogenous reader beliefs. It also provides a tool to monitor reader beliefs and to help publishers to slant the news items to cater to the readers' aggregate beliefs.

Keywords: Mass media, social media, media bias, confirmation bias

Introduction

One of the crucial functions of the Internet is to empower people to provide feedback (Dellarocas 2003; Dellarocas and Wood 2008; Resnick et al. 2000). But there is a dark side of this function of the Internet (Bolton, Katok, and Ockenfels 2004; Dellarocas 2003). This paper focuses on one aspect of this dark side: how demand-driven media bias that can emerge from social media. Publishers and readers have different goals. Readers desire to acquire accurate, timely, and complete information from media. They want (or claim to want) truthful information, information that is free from biases. Publishers understand the industry is heavily viewership-driven, based on revenues derived from subscriptions and advertising. Paradoxically, listening too much to their readers may drive media channels away from selecting, discussing and presenting the unbiased news items. Why? Because these channels can use, for example social media, to easily monitor what readers respond to – what they truly want versus what they say they want – and, as a result, they tend to distribute news items that please readers in the short term. It is possible that readers desire truthful news in the end, but respond more immediately to sensationalistic news (Loewenstein 2006). Clicking on a sensational story does not necessarily mean that the reader no longer wants accurate news.

Social media can track people's attitudes towards events, people or organizations. Relying too much on social media can lead to bias in traditional media. That is, mass media may monitor social media and accordingly please readers with news articles slanted toward viewer interest. Readers will consume the biased news, which can in turn affect their decision-making. In this paper, we describe one working mechanism that makes the demand-driven media bias possible, and we show evidence for its existence.

We base this study of media bias on an online stock news platform. Stock news has real impact on consequential decisions made by readers. The dataset we study contains both traditional media news stories generated about stocks by publishers, as well as social media microblogs generated by stock investors. Specifically, we have data from both Sina Weibo and Sina Finance in the Chinese market. Sina is a telecommunications company. Sina Finance is an Internet news platform. It includes almost all public financial information available on the Chinese stock market. Sina Weibo is a microblogging service similar to Twitter. Our original dataset includes all financial news (4.27 million pieces of stock news) and weibos associated with stocks (43.17 million stock-related weibos) for the years 2013 and 2014. The Chinese stock market is also an ideal market for our study because most of the information recipients in this market are individuals. According to the China Securities Depository and Clearing Corporation Limited, as of the end of 2014, more than 99.6% of investors, or 72.71 million, in the Chinese stock market were individuals.

In the empirical tests, we find evidence that news items on a particular stock that are consistent with the beliefs presented in Weibo receive more clicks at the aggregate level. We assume the sentiment of the microblogs express the investors' true feelings about companies and about companies' future prospects. We then scrutinize the presence of media bias, which can be seen if investors' beliefs at day t-1 can predict the sentiment of traditional news articles at day t.

Conceptual Foundation

The Role of IT in Facilitating Media Bias

Mass practitioners have been encouraged to leverage the crowd's preferences: Miranda, Young, and Yetgi (2016) argue that social media constitute a kind of democratic feedback that may balance any biases that mass media publishers have. Xu and Zhang (2013) say that Wikipedia, because it captures the crowd's collective perception of the world, can correct any dysfunctionality of mass media, thereby improving the information environment. This optimistic stream of literature implies that mass media and social media are independent of each other.

But they affect each other. Media channels use social media such as Twitter as an information source and extract interesting content from them. For example, in the CNN iReport the audience become reporters and submit to the online portal of CNN their chosen news materials to be distributed on TV. A Twitter video about a passenger being violently dragged from a United Airlines overbooked flight motivated the recent heavy coverage of this story on TV.[1] Moreover, mass media channels use the Internet to calibrate the attitude of their readers. For example, BBC provides a world news forum for the readers to discuss specific topics and reports on readers' opinions. Online news aggregators also empower users to select and display news articles that they "like" the most, for example, on Digg.com. On the one hand, mass media channels track readers' preferences and respond to them, potentially creating media bias. On the other hand, readers read news from mass media and apply what they learn to their decisions. As the mass media channels increasingly rely on IT, social media provide a tool for mass media to better understand market demand.

Facilitating Confirmation Bias at the Aggregate Level

Prior literature has discussed confirmation bias: individuals overvalue confirmatory information while devaluing other information (Nickerson 1998). The presence of confirmation bias at the individual level, however, does not imply that readers as a group exhibit confirmation bias. For example, if readers hold prior beliefs in a randomly distributed way, their desire to read confirmatory information may be cancelled out. In aggregate, there is no shift in viewership toward a particular sentiment related to the article. Mullainathan's model (2005) clearly shows that media accuracy is a function of reader belief heterogeneity: only when readers share common beliefs do the mass media provide information that exhibits systematic bias. If investors share a common belief, then mass media slant news toward this common belief and in this way systematic bias emerges.

Social media in fact encourage homogeneous beliefs among readers. Readers can exchange their private information and opinions through various online channels, particularly through social media (Antweiler and Frank 2004; Chen et al. 2014). With exposure to others' opinions, people tend to converge toward the majority opinion - people are subject to social influence (Asch 1955; Muchnik, Aral, and Taylor 2013). Specific to the stock market, stock prices change quickly and the quick change of price can create randomness in people's individual opinions. For this reason, it is rare for investors to have a persistent and strong belief about a particular stock over time. Because most investors do not have persistent and

[1] United Airlines Passenger Is Dragged from an Overbooked Flight, the New York Times, April 10, 2017

strong prior opinions about stocks, they are susceptible to social influence, which leads to one majority opinion in the stock market. In fact, the finance literature has documented the herding effect: investors tend to listen to each other when considering investment choices, which leads to group think (Wermers 1999; Welch 2000; Graham 1999). This phenomenon is particularly apparent in the Chinese stock market (Tan et al. 2008; Chiang, Li, and Tan 2010). Moreover, Antweiler and Frank (2004) provide empirical evidence that the effect of disagreement among the posted messages in the social media on the stock market is short-lived, lasting no more than one day.

Because of this, we hypothesize that social media can help converge investors' beliefs to one majority belief in the stock market setting. This is in contrast to other settings. For example, in United States politics, social media enable social influence and may facilitate the conversion of individual opinions into two extremes of opinions at the aggregate level (Colleoni, Rozza, and Arvidsson 2014). In other words, the number of distinct aggregate opinions facilitated by social media can vary depending on the situation. Pertinent to this case, empirical evidence suggests individuals will converge toward one aggregate opinion with respect to stocks. We propose that confirmation bias will exhibit itself at the aggregate level in the setting of the stock market:

Hypothesis 1 (The Confirmation Bias Hypothesis) A stock news article will receive more clicks when its sentiment is consistent with investors' aggregate stock preference from social media.

The above confirmation bias can encourage mass media to slant news articles to cater to what readers want to read. This is demand-driven media bias. Media bias has been the subject of many studies (Gentzkow and Shapiro 2010; Gentzkow et al. 2015; Puglisi and Snyder 2015; Mullainathan and Shleifer 2005; Xiang and Sarvary 2007). Media bias in our paper does not necessarily imply that the news reported by mass media is fake. Rather, mass media may selectively report (or ignore) news that is favorable (or unfavorable) to their own interests. These are sins of omission and commission. Also, mass media may explain the same piece of news in a way that is favorable to their interests. That is, they may slant the language of a report in order to elicit particular emotional responses (Mullainathan and Shleifer 2005; Gentzkow and Shapiro 2010). Mass media pursue viewership as they gain revenues based on subscriptions and advertisings. In order to maximize their viewership and profit, media channels can use social media to understand what readers want. They then may provide news items in a way that caters to readers' belief, and consequently, demand-driven media bias emerges (Mullainathan and Shleifer 2005; Xiang and Sarvary 2007; Gentzkow and Shapiro 2010). This leads to the following hypothesis.

Hypothesis 2 (The Media Bias Hypothesis) Investors' aggregate stock preference affects stock news sentiment.

Data

To examine our proposed media bias, we analyzed data from Sina Finance - a finance news platform that creates and distributes its own stock news and mainly distributes stock news from other sources - and Sina Weibo, a microblogging service in China. In the following sections, we detail the data-collection process and our measurement techniques.

Investor belief (Social Media Stock Preference)

We use investor belief obtained by Sina Weibo to proxy for the beliefs of investors. We collected microblogging data from Sina Weibo from 2013 and 2014. As reported in the 2015 annual report of Sina, Sina Weibo's operating company, as of December 2015, Sina Weibo had 235.7 million monthly active users and an average of 106.3 million daily active users. Weibo is considered the most influential microblogging platform in China (Harwit 2014). Sina provided us with the original sentiment data. The company first extracted all microblogs that mentioned Chinese stocks by using Ticker and Jiancheng, (an abbreviated stock name in Chinese), during 2013 and 2014. Then the company used its proprietary sentimental dictionary to measure the sentiment of microblogs. The company used 1, 0, and -1 to indicate positive, negative, and neutral sentiment, respectively. As previously stated, our original dataset includes more than 43.17 million microblogs from January 2013 to December 2014, each of which refers to at least one stock. We calculated investor belief following Antweiler and Frank (2004):

$$B_{i,t} = ln\,(\frac{1+n_{i,t}^{P}}{1+m_{i,t}^{N}}) \qquad (1)$$

where $B_{i,t}$ is the proxy for investor belief on stock i at day t, and $n_{i,t}^{P}(m_{i,t}^{N})$ is the number of microblogs with positive (negative) sentiment for stock i at day t. Our database contains 1,436 million stock-day observations.

Information Sentiment (News Article Sentiment)

Sina provided us with more than 6.2 million news items for 2013 and 2014, 4.27 million of which mention at least one stock. Some news items provided by Sina mention several stocks. For example, every morning Sina Finance creates and displays a news item that summarizes all stock-related announcements from companies. In these summaries, a different sentiment may be conveyed about each stock: some are positive and some are negative. We suspect that the sentiment of one stock may affect the sentiment of another stock in the same news story. Because of this, we retained information that mentions only one stock, narrowing down our database to 3.46 million information items. It is also important to note that information in our dataset refers not only to news reports from published mass media but also to company announcements and financial analyst reports. We define *information* in our dataset as all published information regarding each stock. Sina provided information sentiment in a similar way to the investor belief of Weibo. Following Equation 1, we calculated the "information sentiment" ("*InfoSent*") for each stock. Specifically,

$$IB_{i,t} = ln\,(\frac{1+in_{i,t}^{P}}{1+im_{i,t}^{N}}) \qquad (2)$$

where $IB_{i,t}$ is the proxy for information sentiment on stock i at day t, and $in_{i,t}^{P}$ ($im_{i,t}^{N}$) is the number of news items with a positive (negative) sentiment for stock *i* at day *t*. We convert our data from the news item level to the stock-day level.

Information Viewership (News Article Viewership)

Following Park et al. (2013), we used the natural logarithm of one plus the number of clicks on the information to measure information viewership, that is,

$$IV_i = \ln(1 + PV_i) \qquad (3)$$

where PV_I is the number of clicks on information *i*.

Control Variables

Our control variables are size, PB, ROE, past stock return, and past information sentiment. "*Size*" is defined as the natural logarithm of one plus the number of shares times the closing price; "*PB ratio*" is the price-to-book ratio, estimated as the market capitalization over company net assets; "*ROE*" is the return on equity, calculated as the net profit over the shareholders' equity; past stock return, "*CumRet*," is the cumulative return over the past five days. Past information sentiment, "*InfoSent (t-n)*," is the *n* day lagged information sentiment.

Empirical Analyses and Results

To test the first hypothesis, we regressed information viewership ("*InfoView*") on aggregate investor belief ("*InvBel*") at *t-1*, information sentiment ("*InfoSent*"), and their interaction term - that is:

$$InfoView_i = \alpha + \beta_1 InvBel_i + \beta_2 InfoSent_i + \beta_3 InterTerm_i + \beta_4 Control\ Variables_i \qquad (4)$$

where $InfoView_i$ is the natural logarithm of one plus the number of clicks on the information i; $InvBel_i$ is the investor belief for the stock mentioned in information *i* at day *t-1*; $InfoSent_i$ is the information sentiment for information i; $InterTerm_i$ is the product of $InvBel_i$ and $InfoSent_i$; Control Variables include size, PB ratio, ROE, past stock return, and lagged "*InfoSent*". Model (1) in Table 1 shows the results.

	Model (1)		Model (2)	
	Coef.	t-stat	Coef.	t-stat
InvBel	-0.0003	-0.05	0.001	0.16
InterTerm	0.08***	15.72	0.08***	13.67
InfoSent	-0.14***	-10.32	-0.04***	-3.53
CumRet	1.56***	14.87	1.58***	14.64
Size	0.15***	5.76	0.15***	5.61
PB	-0.0004**	-2.35	-0.0004**	-2.52
ROE	-0.0001	-1.70	-0.0001*	-1.77
Cons	-1.23**	-2.07	-1.18*	-1.94

Table 1. Confirmation bias and information viewership

Notes: The regressions incorporate daily fixed effect. *, **, and *** denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

Our main variable of interest is the interaction term. The interaction term measures the consistency of lagged investor belief and information sentiment. When both variables have the same direction, i.e., both are positive or negative, the value of the interaction term is positive, and vice versa. The coefficient on the interaction term is significantly positive. The result shows that a piece of information receives more clicks when the attitude expressed is consistent with one-day-lagged investor belief. This result supports Hypothesis 1 (the confirmation bias hypothesis).

In addition, Model (1) in Table 1 also presents an extra interesting result: "*InfoBel*" is negatively and significantly correlated with the number of clicks on the information, suggesting a negativity-bias effect: on average, investors value negative information more than positive information.

We wanted to test for the effects of lags: both information sentiment and investor belief might be driven by the lagged information sentiment in previous periods. To address this concern, we first regressed investor belief at *t* on information sentiment from the past five periods. Then we obtained the residual from the regression as the proxy for our new measure of investor belief. This new measure excludes the impact from previous news sentiment. We re-ran the regression in equation 4. Model (2) in Table 1 shows the results. The results are similar to those shown in Model (1).

Hypothesis 2 states that investors' collective stock preferences affect stock news sentiment. We hypothesize that in order to attract more clicks mass media purposely create, display or explain information in a way consistent with investors' previous beliefs. This hypothesis predicts 1) publishers slant the stories toward investors' beliefs; and 2) as a result, stories will exhibit bias. In this section, we test these two predictions separately.

We test the first prediction by examining whether investor belief for stock *i* at day *t-1* forecasts information sentiment for stock *i* at day *t*. Specifically, we regressed information sentiment ("*InfoSent*") for stock *i* on day *t* on the one-day-lagged investor beliefs ("*InvBel*") and other control variables:

$$InfoSent_{i,t} = \alpha + \beta_1 InvBel_{i,t-1} + \beta_2 Control\ Variables_{i,t-1} \qquad (5)$$

where $InfoSent_{i,t}$ is the information sentiment for stock *i* at day *t*; $InvBel_{i,t-1}$ is the investors' aggregate belief for stock *i* at day *t-1*. We control for the information sentiment during the past seven days. The other control variables include size, PB ratio, ROE, cumulative stock return over the past five days and lagged information sentiment.

Table 2 shows the results. In Model (1), the coefficient on investor belief at *t-1*, $InvBel_{i,t-1}$, is significantly positive, suggesting a positive association between lagged investor belief and information sentiment. The information sentiment tends to be consistent with lagged investor beliefs. The results support H2 (the media bias hypothesis).

	Model (1)		Model (2)		Model (3)	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
InvBel (t-1)	0.01***	13.9	0.01***	17.68	0.02***	12.1
InvBel (t-2)			-0.0006	-1.06		
InvBel (t-3)			0.00	-0.07		
InvBel (t-4)			0.0006	0.95		
InvBel (t-5)			-0.0005	-0.84		
InvBel (t-6)			-0.002***	- 3.39		
InvBel (t-7)			-0.001***	-2.67		
CumRet	0.06***	5.5	0.07***	6.06	0.07***	3.56
Size	0.05***	19.46	0.05***	19.36	0.05***	17.75
PB	0.00	1.28	0.00	1.22	0.00	1.44
ROE	0.00	0.81	0.00	0.77	0.00	0.85
InfoSent (t-1)	0.24***	82.06	0.24***	82.38	0.34***	28.02
InfoSent (t-2)	0.07***	19.05	0.07***	19.01	0.12***	19.49
InfoSent (t-3)	0.08***	25.28	0.08***	25.11	0.09***	21.76
InfoSent (t-4)	0.06***	20.97	0.06***	20.85	0.06***	15.24
InfoSent (t-5)	0.06***	21.88	0.06***	21.76	0.05***	13.60
InfoSent (t-6)	0.05***	20.53	0.05***	20.52	0.05***	12.47
InfoSent (t-7)	0.07***	22.23	0.07***	22.20	0.07***	14.83
Cons	-1.2248***	-19.63	-1.23***	-19.43	-1.23***	-17.82
Num of Obs	1,074,393		1,074,393		205,896	
Adjusted R2	0.17		0.17		0.18	

Table 2. Information sentiment and investor belief

Notes: The regressions incorporate daily fixed effect. Standard errors are clustered at the stock level. *, **, and *** denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

We also predicted that news articles as a result are biased. Chen et al. (2014) explicitly showed that some information in the social media can predict future firm performance and conclude this information is (1) representative of the fundamental values of stocks and (2) not currently incorporated into prices. If media channels only report the accurate private information, the association between investor belief and information sentiment is driven by the "value-relevant" information. Specifically, investor belief is correlated with information sentiment because both reflect "value-relevant" information, not because biased investor belief affects information sentiment as we suggested. Because of this, we conducted three tests to verify that (some) investor belief is, at least partially, noisy (i.e., not related to fundamental values of stocks) in our dataset (Models (2) and (3) in Table 2, and Table 3). In Model (2), we follow previous literature, as described below, and test whether the association between investor belief and information sentiment has a reversal effect in a longer horizon. In the last test, we test a joint hypothesis that information distributed in mass media is biased and that this bias results from mass media trying to maximize their viewership.

Previous studies rejected the hypothesis that information only contains "value-relevant" information by showing a reversal effect: Tetlock (2007) and García (2013) argued that if investor belief was noisy, one would predict a positive association between investor belief and stock return in the short run, and predict a reversal effect - that is, a negative association - in the long run. Following this logic, we regressed information sentiment on investor belief for a longer horizon. We hypothesized that our investor belief may positively predict news sentiment in the short term and negatively predict it in the long term. A simple example is that a company may later deny some rumors that were reported several days before. Model (2) in Table 2 shows a clear reversal effect from *t-2* to *t-7*, even though the coefficients from *t-2* to *t-5* are not significant.

Some other studies examined the association between investor beliefs on Sundays and stock returns on Mondays (García 2013; Siganos, Vagenas-Nanos, and Verwijmeren 2014) . García (2013) argued that value-relevant information is less likely to arrive during weekends; as a result, investor belief on Sundays are less likely to be associated with the value-relevant information. Therefore, if mass media only follow accurate information in social media, we should observe no association or a weaker association between investor belief on Sundays and information sentiment on Mondays.

Following this logic, we tested whether investor belief on Sundays affects information sentiment on Mondays. Specifically, we repeat the regression in equation 5 with a news article sample from Mondays (*t*) and a social media sample from Sundays (*t-1*). Model (3) shows the results. The coefficient of investor belief at *t-1* is 0.02, which is larger than 0.01 in Model (1). The results are consistent with our prediction.

To further explore whether information is biased and this bias is driven by the pursuit of viewership, we examine whether media bias varies across the media channels with different sources of revenue. If some mass media do not depend on viewership to obtain revenue, we would expect they exhibit a less severe form of media bias. Some mass media in our database – *China Securities Journal, Shanghai Securities News, Securities Times, Cninfo, and their affiliated entities* – are Designated Information Revealing Media (DIRM), as determined by the regulator, the China Securities Regulatory Commission. All listed companies and financial products traded in the stock market are obligated to publish announcements through these media channels. A large portion of their revenue comes from publishing such announcements. We expect that the publishers classified as DIRM have less motivation to cater to readers than other publishers.

We divided our sample into two categories according to whether the mass media are DIRM and then calculate information sentiment for both categories. Our hypothesis predicts that aggregated investor belief has a better predictive ability for information sentiment estimated by the non-DIRM mass media than that by the DIRM mass media. Table 3 presents the results.

	Model (1)		**Model (2)**		**Model (3)**		**Model (4)**	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
InvBel (t-1)	0.003***	9.11	0.003***	11.40	0.004***	6.61	0.005***	9.21
InvBel (t-2)			-0.0001	-0.41			-0.0006	-1.26
InvBel (t-3)			-0.0006**	-2.02			0.0002	0.34
InvBel (t-4)			0.0004	1.26			0.0005	1.01
InvBel (t-5)			-0.0002	-0.85			-0.002***	-4.48
InvBel (t-6)			-0.0008***	-2.69			-0.0002	-0.38
InvBelt (t-7)			-0.0007***	-3.00			-0.001***	-3.47
CumRet	0.05***	10.17	0.05***	11.37	0.04***	3.97	0.04***	4.49
Size	0.01***	11.47	0.01***	19.36	0.03***	12.28	0.03***	12.23
PB	-0.00	-1.18	-0.00	-1.21	-0.00	- 0.48	-0.00	- 0.52
ROE	-0.00	-1.55	-0.00	-1.52	-0.00	-0.71	-0.00	-0.68
InfoSent (t-1)	0.07***	43.45	0.07***	43.55	0.12***	41.08	0.12***	41.25
InfoSent (t-2)	0.006***	3.89	0.006***	3.9	0.04***	12.96	0.04***	13.00
InfoSent (t-3)	0.01***	8.57	0.01***	8.52	0.05***	16.07	0.05***	15.91
InfoSent (t-4)	0.008***	6.38	0.008***	6.31	0.04***	14.18	0.04***	14.07
InfoSent (t-5)	0.009***	6.89	0.009***	6.86	0.04***	13.12	0.04***	13.14
InfoSent (t-6)	0.008***	7.25	0.008***	7.34	0.03***	14.45	0.03***	14.54
InfoSent (t-7)	0.007***	6.90	0.008***	7.02	0.04***	15.10	0.04***	15.05
Cons	-0.3***	-13.03	-0.3***	-12.68	-0.71***	-12.65	-0.72***	-12.48
Num of Obs	1,050,959		1,050,959		1,050,959		1,050,959	
Adjusted R2	0.06		0.06		0.12		0.12	

Table 3. Information sentiment and investor belief

Notes: The regressions incorporate daily fixed effect. Standard errors are clustered at the stock level. *, **, and *** denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

The dependent variables in Models (1) and (2) describe information sentiment estimated by the DIRM; and those in Models (3) and (4) are estimated by the non-DIRM mass media. Following Huang et al.

(2015), we compared the R-square values in those regressions to examine the predictive ability of investor belief. The R-square values in Models (3) and (4) are much larger than those in Models (1) and (2), suggesting that investor belief has a stronger ability to predict the information sentiment of non-DIRM information than that of DIRM information. The results are consistent with our predictions.

We used bootstrapping to alleviate concern about large samples and p-value tests (Lin, Lucas, and Shmueli 2013). Bootstrapping is a statistical technique that resamples our observations in regressions (Efron and Tibshirani 1994). It reports the distribution of coefficients. We ran all our regressions using this technique and all our conclusions stand.

Implications and Limitations

There has been much discussion related to news and its effects on human behavior and, of late, voting behavior (Wessel 2017; Bohannon 2017; Gentzkow, Shapiro, and Stone 2015; Puglisi and Snyder 2015). In this study, we examined demand-driven media bias in the financial context. But there may be broader applications to our findings. Specifically, media channels want to increase viewership, and so they leverage social media to select and slant news in order to appeal to more viewers. But viewers suffer from confirmation bias, so they tend to read what they already believe. This sets up a dangerous feedback loop. For example, media channels may recognize that investors are bullish about the market, and so they will publish stories with more positive sentiment. Investors who are positive select this material to read, which reinforces their belief. Moreover, even rational investors may be taken in, as the news itself becomes mostly biased and it is costly to find unbiased news, disturbing rational decision-making processes (French 2008; Fang, Peress, and Zheng 2014). The term echo chamber has been used to qualitatively describe this phenomenon when applied to social news. But the term is probably also accurate in relation to finance. If true, it makes accurate news extremely valuable: rational investors would be well served by finding news sources that are not incentivized to reflect and amplify readers' beliefs.

This paper has strong research and practice implications. First, this paper highlights the formation and danger of media bias specific to the stock market. In the stock market, information that is valuable in one second can be worthless in the next. Therefore, it is essential for the online financial news platforms, such as Yahoo! Finance, to reduce (or eliminate) media bias and to distribute timely unbiased information to investors. Second, current investor education emphasizes an understanding of finance market products and risk management. But our research suggests it is also important for investors to learn to differentiate stock-market-related information that is based on attempts to garner readership from information that is more likely to convey the underlying value of an asset. Readers’ desire for unbiased information and publishers’ desire for readers should theoretically create a marketplace for unbiased information. If this does not work, then some kind of regulation may be necessary to insure there are affordable sources of unbiased information for those who seek it.

In the setting of the stock market, we conjectured that social media help converge individual opinions into one majority opinion; we conducted an additional test to suggest that investors’ beliefs have such a unimodal distribution. We followed Anterweil and Frank (2004) and defined a new variable called *Disagreement* to show the distribution of the investors’ beliefs. The variable is defined as:

$$\text{Disagreement} = 1 - \sqrt{(1 - \left(\frac{M_p - N_n}{M_p + N_n}\right)^2} \qquad (6)$$

Where M_p is the number of the positive weibos and N_n is the number of negative weibos on stock i at day t. Disagreement ranges between zero and one. A value of zero means M_p and N_n are the same and suggests the highest level of disagreement. A value of one suggests the highest level of agreement regardless of investors’ beliefs (positive versus negative). We found 59.1% of the observations are 1. And 75% of observations have a value larger than 0.3. This finding suggests that in the setting of the stock market, investors tend to achieve agreement more than disagreement. In other settings where individual opinions converge into multiple opinions such as in democratic politics, multiple echo chambers may exist, amplifying multiple pre-beliefs. In such cases, mass media can cater to these different groups of opinions and create various media biases driven by different market demands.

Our paper has several limitations. First it doesn't examine causality. This paper provides empirical evidence to suggest one possible working mechanism that makes demand-driven media bias possible. Second, we tested our hypotheses using data from the Chinese stock market. One reason for this choice of market is that individual investors are dominant in the Chinese stock market. By contrast, a larger proportion of investors in the United States (US) market are institutional investors, who are more likely to spend time on acquiring information and building analytic skills. By this reasoning investors in the Chinese market may, on average, be less sophisticated, or spend less time acquiring information, than investors in the US market. Our research calls for studies that aim to replicate our results in different stock markets and, more importantly, examine the extent to which media bias exists in, and influences, these stock markets.

Conclusion

Without social media, it is time consuming for media channels to collect data related to market demand and then react to it. We showed that social media can facilitate media bias. This should alarm practitioners: the use by traditional media of social media to monitor what customers want may have negative consequences. For example, negative consequences of a similar phenomenon with respect to stock price has been documented by Tetlock (2007) and García (2013). This paper provides empirical evidence for demand-driven media bias. Social media provides a way to monitor consumer sentiment in real time and pander to it. While we may expect advertisers to immediately avail themselves of this data, we may hope that traditional media would be more restrained.

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