Sentiment Change and Negative Herding: Evidence from Microblogging and News

Abstract

Companies deal with good and bad publicity daily. We study the impact of news on consumer sentiment toward a company in the presence of pre-news sentiment. We use Sina Weibo's (the Chinese version of Twitter) microblogging data and the full list of news items published in Sina Finance between 2013 and 2014 to measure sentiment. In our study, we address the following research questions: Does negative news have a greater impact than positive news on consumer sentiment change? Does news affect sentiment change to a greater degree when pre-news sentiment matches the news valence? Does the type of company (either B2C or B2B) matter? Our empirical findings show that consumers overreact to negative news and negative pre-news sentiment intensifies such overreaction, leading to negative herding. Further, negative pre-news sentiment is even more damaging for B2B companies than for B2C companies.

Keywords: consumer sentiment, negativity effect, herd behavior, negative herding, microblogging, B2C versus B2B.

Introduction

Companies constantly deal with publicity that affects consumer sentiment, be it announcements of favorable quarterly earnings (Mian and Sankaraguruswamy 2012) or high profile corporate scandals (Dean 2004; Meijer and Kleinnijenhuis 2006). As such, it is imperative to understand how a market reacts to such news in a way that results in a significant change in company value (Baker and Wurgler 2006; Brown and Cliff 2005; Lemmon and Portniaguina 2006). Prior literature documents macroeconomic evidence based on singular events (Garner 2002; Throop 1992) and specific situations (Conrad, Cornell, and Landsman 2002; Hong and Lim 1998; Meijer and Kleinnijenhuis 2006). However, to the best of our knowledge, little systematic investigation has been done on how the effect of news on consumer sentiment varies across companies and over time.

We are especially interested in the role of pre-news sentiment regarding a company. By pre-news sentiment, we mean collective public sentiment toward a company before the news hits the market. This concept is closely related to brand attitude, a persistent evaluative judgment toward a brand (Dick and Basu 1994). Also, prior studies show that in addition to the news itself, social influence or herding may guide the development of a strong collective sentiment toward a company (Cheung and Thadani 2012; Lee, Hosanagar, and Tan 2015).

Our research begins with a consideration of the asymmetric effects of news valence on consumer sentiment. Prior research shows that negative information has a greater impact than positive information of similar importance (the negativity effect, Rozin and Royzman 2001). This phenomenon is observed in various domains, including purchase decisions (East, Hammond, and Lomax 2008), stock trading (Tirunillai and Tellis 2012), and judgment (Ahluwalia 2002). As such, companies should put more effort into countering bad publicity than they normally exert in promoting favorable publicity.

We further conjecture that pre-news sentiment can moderate the impact of news valence on consumer sentiment. That is, pre-news sentiment interacts with news valence in a way that results in an asymmetric consumer response: the negativity-herding interplay. We argue that negative news affects sentiment more when pre-news sentiment is negative, an effect we call *negative herding*. Directionality in herding is interesting and relevant because it promotes not only a theoretical understanding of herd behavior but also helps managers predict and manage business outcomes based on pre-news sentiment. For instance, if the stock market presents negative herding, investors can expect that stocks will be undervalued immediately after bad news because herding increases the sensitivity of stock prices to bad news.

The type of company involved, in terms of being consumer-oriented (B2C) or business-facing (B2B), is also a key factor affecting consumer sentiment. Consumers are more familiar with B2C companies (Glynn 2012), or so they believe. They are less familiar with B2B brands and are less confident of their knowledge of them. Because consumers trust their own judgment more on topics about which they feel most knowledgeable (Facione et al. 1995), official news about B2C companies will have a greater impact on post-news sentiment and pre-news sentiment (i.e., others' opinion) will have a lesser impact. Conversely, pre-news sentiment toward B2B companies may have a greater impact on the response to the news because consumers are inclined to defer to the opinions of others on unfamiliar topics (Hochbaum 1954).

We focus on consumer sentiment rather than often-used measures such as sales or stock returns for several reasons. Consumer sentiment has been solidly linked to other outcome variables of interest, such as stock prices (Baker and Wurgler 2006) and sales (Gopinath, Thomas, and Krishnamurthi 2014). If sentiment is one of the fundamental drivers of these outcomes, it would be useful to understand this component in isolation from other possible inputs. In addition, we now have available a ready source of data that is a reliable measure of consumer sentiment, namely microblogging data (Bollen, Mao, and Zeng 2011; Deng et al. 2018). In the past, consumer sentiment was not easily observed because of the difficulty of collecting data to measure it (Baker and Wurgler 2007). With the proliferation of real-time microblogging and the development of techniques such as sentiment analysis, we can now observe consumers' overall sentiment (Da, Engelberg, and Gao 2014; Siganos, Vagenas-Nanos, and Verwijmeren 2014; Sprenger et al. 2014).

Therefore, our research makes several theoretical contributions to the literature on consumer sentiment and social influence as follows.

1. We fill the gap in the literature on the effect of news by investigating how news affects changes in *consumer sentiment* toward a company, rather than widely-researched firm performance values such as sales or stock return, using a large microblogging data set.
2. We first document an overreaction to negative news in consumer sentiment change when the news valence matches the pre-news sentiment and explore *herding*, a social influence, as one of the potential underlying mechanisms.
3. We examine the moderating role of the type of company involved (B2C vs. B2B) on the news effect and herd behavior in consumer sentiment change.

Our empirical analyses use datasets collected from two distinct sources between 2013 and 2014. The first is full-sample microblogging data on stocks from Sina Weibo (Weibo for short), the Chinese equivalent of Twitter, and the second, the entire list of news items from Sina Finance, a financial news aggregator in China. A microblogging service such as Twitter is considered a comprehensive and accurate source to measure consumer sentiment (Deng et al. 2018; Pak and Paroubek 2010; Rambocas and Gama 2013) as well as a unique platform that disseminates information in a viral manner (Stieglitz and Dang-Xuan 2013).

Empirical findings show that consumers overreact to negative news, and this reaction is enhanced when pre-news sentiment is negative (negative herding). However, such an overreaction to positive news (positive herding) does not occur for a company with the positive pre-news sentiment, perhaps because the market is predominantly populated with positive sentiment and positive news. This phenomenon is clearly present for B2B companies, a category of business with which consumers have relatively little knowledge and familiarity compared to B2C (Leek and Christodoulides 2011). We provide support for the proposed herding mechanism through the use of a novel variable: Weibo by verified users. We also document that the herding phenomenon persists over time.

The rest of the paper is organized as follows. In Literature and Hypotheses, we summarize prior studies and suggest our hypotheses. We then introduce our data, explain measures, and describe models. In Empirical Findings, we test our hypotheses and examine additional impacts both over time and on stock returns. Finally, we summarize our findings and suggest their implications for managers.

Literature and Hypotheses

Based on the literature on consumer sentiment and the role of news valence, we propose hypotheses describing sentiment changes after news announcements and the moderating role of pre-news sentiment and company types. See Figure 1 for the conceptual framework.

[Insert Figure 1 about here]

Consumer Sentiment

Consumer sentiment has been a topic of great interest to various constituencies, including policymakers, managers, and academics, because it is predictive of numerous phenomena. For instance, consumer sentiment is closely tied to global risk premia (Keiber and Samyschew 2015), rates of crime (Rosenfeld and Fornango 2007), asset returns (Baker and

Wurgler 2006), household spending (Carroll, Fuhrer, and Wilcox 1994), sales (Sonnier, Mcalister, and Rutz 2011), election results (Bohannon 2017), and box office success (Chintagunta, Gopinath, and Venkataraman 2010). However, few studies have been done on what affects this sentiment except the gathering of some sporadic macroeconomic evidence based on singular events (Garner 2002; Throop 1992). This is partly because of the difficulty in measuring sentiment (Baker and Wurgler 2007; Qiu and Welch 2004). In the past, researchers resorted to nationwide consumer surveys (Lemmon and Portniaguina 2006) or indirect measures such as discounts of closed-end funds (Brown and Cliff 2005), both of which can be costly to collect or can have low construct validity. With the proliferation of social media such as Twitter and Facebook and more access to big data such as Google's search volume, we now have a relatively inexpensive and direct measure of consumer sentiment (Bollen, Mao, and Zeng 2011; Da, Engelberg, and Gao 2014; Sprenger et al. 2014; Stieglitz and Dang-Xuan 2013). In our context, consumer sentiment is defined as the collective attitude of consumers toward a company or a brand. The particular focus is on the effect of news on the resulting consumer sentiment in the presence of existing sentiment.

Negativity Effect

Prior studies in psychology and consumer behavior have well documented that information of negative valence is weighted more heavily in consumers' judgment than one with a positive valence of equal importance: that is, the negativity effect (Ahluwalia 2002; Mizerski 1982; Vaish, Grossmann, and Woodward 2008). Indeed, consumers' observable tendency to overreact to negative information occurs in many contexts. Specifically, negative cues about a new acquaintance weigh more heavily in impression formation (Park and Lee 2009; Skowronski and Carlston 1987); the impact of negative reviews for films or books is greater than that of positive reviews (Basuroy et al. 2003; Chevalier and Mayzlin 2006);

negatively framed messages are more effective (Shiv, Edell Britton, and Payne 2004) and result in a greater attitudinal change (Ahluwalia, Burnkrant, and Unnava 2000). Furthermore, negative information such as product failure is more diagnostic than positive product information in a product evaluation process (Herr et al. 1991). Hence, negative information receives greater weight when evaluating and making decisions related to a product or company. Negativity effect is also observed in a financial market: negative news leads to more trading volume in stock markets (Tirunillai and Tellis 2012) and undermines company performance to a greater degree (Luo 2008). There is even neurological evidence that negative stimuli create greater brain activity in the corresponding cerebral regions (Vaish, Grossmann, and Woodward 2008).

Some studies report the opposite: Positive information is weighted more heavily than negative information of comparable impact (Muchnik, Aral, and Taylor 2013; Klayman and Ha 1987; Yin, Mitra, and Zhang 2016). However, positivity effects seem to be context-specific. The evidence suggests that people overreact to positive information when it is self-related because people have strong conscious and unconscious desires to view themselves favorably (Loewenstein 2006; Sicherman et al. 2016). Also, positivity effects are often observed in user review helpfulness literature (Yin, Mitra, and Zhang 2016). Consumers looking to buy a product can do so after they encounter a large enough number of good reviews, not the bad ones, and thus find positive reviews to be more helpful (Zhang, Craciun, and Shin 2010). This leaning toward positivity is driven by motivated reasoning (Kunda 1990), which is that consumers tend to selectively process evidence that helps them achieve their goals.

In our context, we predict the negativity effect will be more pronounced. Consumers consider negative cues to be more diagnostic (Skowronski and Carlston 1987), and a strong aversion to loss drives consumers to avoid negative outcomes to a greater degree (“prospect theory," Kahneman and Tversky 2013; Rozin and Royzman 2001). Some speculate that negativity bias serves an important evolutionary function that allows humans to explore environments while effectively avoiding harmful situations (Vaish, Grossmann, and Woodward 2008). All these strongly support the negativity effect of bad news on post-news sentiment. Our formal hypothesis is as follows.

H_1: Negative news has a greater impact than positive news on sentiment change.

Herd Behavior

When news arrives, consumer sentiment will adjust accordingly depending on the content (Dean 2004). We propose that the existing sentiment toward a company before the news arrives plays a role in consumer sentiment change after the news is posted. Specifically, consumers observe others' opinions in social media and overreact to official news when the news matches the pre-existing sentiment. We further postulate that such overreaction is likely because of herd behavior (Nadeau, Cloutier, and Guay 1993). Studies in herd behavior show that the simple observation of majority opinion leads observers to convert their views to match the consensus (Abrahamson and Rosenkopf 1993; Leibenstein 1950), making the crowd behave like a herd. This phenomenon is observed in many areas around the social sphere (Chiang and Zheng 2010; Hanson and Putler 1996; Sun 2013).

Herd behavior can happen consciously (Devenow and Welch 1996) or subconsciously (Rook 2006). Individuals have limited attention and cognitive capacity and cannot process all the information they receive from the environment (information overload) (Hirshleifer, Lim, and Teoh 2009; Della Vigna 2007). Following others may lead to a better cost-benefit balance than relying entirely on one's own judgment. Also, expressing personal views that reflect majority opinion may increase the credibility of the speaker (Trueman 1994). Behaving like others may even yield profits or prevent losses, as in the case of liquidity traders trading among themselves (Admati and Pfleiderer 1988) or in runs on banks (Diamond and Dybvig 1983).

At the subconscious level, consumers tend to shape their ideas to match the majority views because their perceptions of social reality lead to majority pressures (Martin and Hewstone 2001; Rook 2006), despite private information that refutes them (Zhang 2010). Gibson and Höglund (1992) explain that imitating others is a tool of evolutionary adaptation, which has enabled humans and animals to take advantage of collective social knowledge. Moreover, news valence evokes emotional responses (e.g., fear, disgust) that can be contagious when expressed in public spaces in mass numbers (Hirshleifer and Teoh 2003; Stieglitz and Dang-Xuan 2013). Thus, we predict that if the pre-news sentiment matches news valence, the change in sentiment will be intensified.

The matching of pre-news sentiment and news valence can happen in either direction, positive or negative. Table 1 presents some of the previous empirical works that investigate positive and/or negative herding. For instance, often only the positive outcomes are observed for product choices (Cai, Chen, and Fang 2009) or voting (Kiss and Simonovits 2014); thus, negative behavior is not manifested. On the other hand, bank runs (Chen 1999), a negative herd behavior, happen only in reaction to bad news. There are also a handful of studies documenting both positive and negative herd behaviors (for instance, Choi, Dassiou, and Gettings 2000 and Lee, Hosanagar, and Tan 2015). Valdés (2000) studies country-level contagion in debt prices after a big event and shows evidence that negative herding is greater in size after negative news than a positive counterpart. Nadeau, Cloutier, and Guay (1993) provide experimental evidence on the bandwagon effect for opinions on social issues. Manipulating the sign of the majority opinion for the same issue (e.g., abortion), they find that the size of herding is about the same in both directions.

[Insert Table 1 about here]

In the context of news announcements and consumer sentiment, herd behavior is driven by the observation of others' opinions in public space, and the negativity effect hypothesized in H_1 applies not only to news but also to informal communications such as word-of-mouth (Tirunillai and Tellis 2012). Thus, others' opinions influence the effect of news, and overall consumer sentiment will lean abnormally more toward the same side as others' opinions before the news releases. Therefore, we hypothesize that

> $H_{2a,b}$: The effect of (a) positive and (b) negative news on sentiment change is intensified when the news valence matches the pre-news sentiment.

The Type of Companies: B2C Versus B2B

Consumers' reactions to the news are affected by many other factors than the news itself and the previous sentiment for a company. Although it is outside the scope of this study to investigate all possible correlates, we propose an important and pertinent factor that can significantly affect the impact of news: This factor is whether the company is a B2C company or a B2B one. Marketing academia considers B2C and B2B customers to operate under different rules when making purchases (Hadjikhani and LaPlaca 2013). Specifically, B2B customers are considered institutional buyers making decisions as a group, but B2C buyers are often individuals making individual decisions (Armstrong et al. 2014). B2B buyers rely less on brands or other emotional aspects and more on functional conditions of the purchase such as price, performance, delivery time, etc. (Mudambi 2002). In B2B industries, the seller-buyer relationship is personal and recursive (Armstrong et al. 2014). Some studies even purport that customer relationship management is really meant for B2B companies and that it often backfires in B2C settings (Dowling 2002). Most notably, B2B companies, because they do not deal directly with consumers, expend considerably fewer resources on consumer marketing than B2C firms do (Leek and Christodoulides 2011). Consequently, consumers generally know less about B2B companies than they do about B2C companies. This situation leads to the next question: For which type of companies are consumers more likely to over- or underreact in terms of processing official news? What about in terms of the reaction to consumer sentiment as opposed to official news?

Consumers are more knowledgeable about B2C companies (Glynn 2012) because of more media exposure (Srinivasan, Lilien, and Sridhar 2011) and firsthand experience with their products (Pansari and Kumar 2017). Because consumers are more confident with the topic, they are more likely to rely on their personal judgment based on official news instead of following popular opinion (Facione et al. 1995; Hochbaum 1954). Consequently, consumers become over-confident in judging veracity from the news coming from an objective source and overreact to the news. When it comes to B2B companies, consumers are less confident of their own knowledge and thus consider all available information, including what others think about the companies (Bonaccio and Dalal 2006). Thus, when there is negative pre-news sentiment for B2B companies, consumers overreact to negative news over and above the immediate reaction to the news. Accordingly, whether the sentiment is positive or negative, pre-news sentiment leads to herding for B2B companies more than for B2C ones. Finally, we predict negative herding will be more pronounced for B2B companies because consumers' tendency to follow majority opinion can also suffer from negativity bias (Valdés 2000). Thus, we propose our hypotheses as follows:

H_{3a}: Negative news has a greater impact on sentiment changes for B2C companies than for B2B companies (i.e., more negativity for B2C companies).

$H_{3b,c}$: The intensified effect of (b) positive and (c) negative news on consumer sentiment change when the news valence matches the pre-news sentiment is less for B2C companies than for B2B companies (i.e., less herding for B2C companies).

Data, Measures, and Model

Data

Our study requires two distinct types of data: one for the news and the other for consumer sentiment. The news data come from Sina Finance, one of the most extensive and influential online news aggregators in China. The original dataset has more than 6.2 million news articles from the years 2013–2014, and 4.3 million of them mention at least one listed company. Since news items mentioning several stocks at once are mostly news about industry trend analysis or overall stock market rather than one specific stock, they are inappropriate to measure the news valence of one specific company. Therefore, following the typical approach in the literature on financial news, we only use news items mentioning one stock. Our final data include 1,134,810 news items that report on 2,547 stocks (which is more than 95% of the active stocks and around 98% of the market capitalization during the sample period). Around 3.8 articles were published for each company per day on average.[1]

Consumer sentiment is extracted from data provided by Sina Weibo, which is the Chinese equivalent of Twitter and by far the most popular domestic microblogging platform (Ge et al. 2017; Harwit 2014). This dataset includes more than 43.2 million "Weibos" (tweets) on at least one listed company for the same time period. For news items and Weibos, Sina uses its proprietary dictionary to calibrate sentiment and conducts text analyses much like other sentiment databases (e.g., Thomas Reuter's Sentiment Index).[2] Sina provided us with the

[1] News from different sources and/or different days are counted as unique news item even if they are reporting the same incident. This approach is appropriate in the news context because repeated reporting of the same news on multiple sources/dates is an indication of the importance of the news and influences changes in the news valence of a company (Fang and Peress 2009).

[2] To verify this measure, we randomly chose 40,000 news items from December 2014 and compared their sentiments with those extracted with third-party software, BosonNLP. The same software has been used in Zheng et al. (2019). The analysis yields an 83% match between Sina's sentiment and our own results, which is an acceptable level (Kharde and Sonawane 2016).

sentiment data (positive, neutral, or negative) for each news item and Weibo.

Measures

Pre- and Post-news Sentiment and Sentiment Change. We use Weibo sentiment as a proxy for consumer sentiment for companies. Previous studies show that the company-specific sentiment of microblogs is a good proxy for the consumer sentiment for that company (Antweiler and Frank 2004; Da, Engelberg, and Gao 2014; Sprenger et al. 2014). Following Antweiler and Frank (2004), we calculate the pre-news sentiment for company *i* on day *t* as follows:

$$(1)\ \mathrm{Pre}_{\mathrm{i,t}} = \sum_{z=1}^{7} \ln\left(\frac{1+\mathrm{n}_{\mathrm{i,t-z}}^{\mathrm{P}}}{1+\mathrm{n}_{\mathrm{i,t-z}}^{\mathrm{N}}}\right)/7$$

where $\mathrm{n}_{\mathrm{i,t-z}}^{\mathrm{P}}$ and $\mathrm{n}_{\mathrm{i,t-z}}^{\mathrm{N}}$ are the number of Weibos with positive and negative sentiment, respectively, for company *i* on day *t* – z.[3] This measure is a weekly moving average of the daily ratio of positive remarks against negative ones based on the volume of messages. We use the rolling average over seven natural days to smoothen daily random noises and rule out day-specific confounding factors that mask the underlying sentiment.[4] Post-news sentiment for company *i* on day *t*, $\mathrm{Post}_{\mathrm{i,t}}$, is measured similarly by using the sentiment of Weibos from *t + 1* to *t + 7*, and thus sentiment change for company *i* on day *t* ($\mathrm{SC}_{\mathrm{i,t}}$) because of news is measured as follows:

$$(2)\ \mathrm{SC}_{\mathrm{i,t}} = \mathrm{Post}_{\mathrm{i,t}} - \mathrm{Pre}_{\mathrm{i,t}}$$

News Valence and Bad. We construct the news valence variable using a similar approach.

[3] We aggregate news sentiment at a daily level on account of general news release/print cycle. This is appropriate since the information given in financial news is incorporated in consumer sentiment and the stock price immediately on the same day.
[4] We conduct robustness tests in which we vary the number of days included in constructing the sentiment and confirm the robustness of our main results (See Appendix Table A.4).

$$(3)\ NV_{i,t} = \ln\left(\frac{1+m^{P}_{i,t}}{1+m^{N}_{i,t}}\right)$$

where $NV_{i,t}$ is the news valence of company *i* on day *t*, $m^{P}_{i,t}$ is the number of news items with positive sentiment for company *i* on day *t*, and $m^{N}_{i,t}$ is the number of negative ones.[5] The resulting measure represents the overall tone and intensity of the major media reporting the events. This variable contains 146,903 company-day observations with positive news valence and 32,667 company-day observations with negative news valence. The negative news valence is further indicated by a dummy variable, $Bad_{i,t}$.

B2C. We construct a dummy variable, $B2C_{i,t}$, that indicates whether a company is considered B2C or B2B. To do so, we first categorize each industry as either B2C or B2B, and then assign each company according to its industry membership. To categorize industries, we use Hoejmose, Brammer, and Millington's (2012) procedure and identify the source of revenue of each industry. They are classified as B2C if the majority of the industry's revenue comes from the consumer market.

The proportion of Weibos by Verified Users. For the test of potential mechanism, we construct a variable $VU_{i,t}$, which indicates the proportion of Weibos tweeted by verified users regarding company *i* on day *t*. In Weibo's user data, we are able to identify "verified users" who have been officially identified by the regulatory authority and are liable to their claims. The accounts of verified users are typically managed by financial experts, such as institutional investors, financial reporters, market analysts, and other recognized opinion leaders. Hence, this variable related to verified users can be a good proxy for the proportion of expert opinions.

[5] The term valence is often used as the manifestation of underlying sentiment (Chintagunta, Gopinath, and Venkataraman 2010) and thus has the connotation of being more observable and objective. In our context, news is an external shock that is based on actual events, thus we find it appropriate to use the term valence.

Control Variables. We include the standard controls used in the financial literature along with company fixed effects. Following Fama and French's (1993) and Carhart's (1997) works, we include company size in terms of the total market value ($Size_{i,t}$), price-to-book ratio ($P/B_{i,t}$), and the past performance of the company's stock ($Cret_{i,t}$). More specifically, $Size_{i,t}$ is the one-day lagged natural logarithm of one plus the product of the number of outstanding shares and the closing price of the stock. $P/B_{i,t}$ is the one-day lagged natural logarithm of one plus the price-to-book ratio. $Cret_{i,t}$ is the cumulative raw return of stock *i* over the past one week.

All the variable definitions and the corresponding summary statistics are reported in Tables 2 and 3, respectively.

[Insert Tables 2 and 3 about here]

Model

We propose two models of consumer sentiment for companies. The fist model tests the average effect of news announcements on sentiment change in the presence of pre-news sentiment. The dependent variable of our models is the change in consumer sentiment from before to after the news ($SC_{i,t}$), and it is regressed on our variables of interest. The second model tests the effects for B2C and B2B companies through incorporating the interaction terms: that is, variables of interest interacted with B2C dummy. We also include other controls as well as day and company fixed effect to account for unobserved daily events and firm-specific idiosyncrasies.

Specifically, Model 1 (equation 4) includes the variable for news valence for company *i* on day *t* ($NV_{i,t}$), a dummy for negative news ($Bad_{i,t}$), pre-news sentiment ($Pre_{i,t}$), and their interaction terms as follows[6]:

$$\text{(4) } \mathrm{SC_{it}} = \alpha_{1t} + \alpha_{1i} + \beta_{1,1}\mathrm{NV_{it}} + \beta_{1,2}\mathrm{Bad_{it}} + \beta_{1,3}\mathrm{Pre_{it}}$$

$$+ \beta_{1,5}\mathrm{NV_{it}} \cdot \mathrm{Bad_{it}} + \beta_{1,6}\mathrm{NV_{it}} \cdot \mathrm{Pre_{it}} + \beta_{1,7}\mathrm{Bad_{it}} \cdot \mathrm{Pre_{it}}$$

$$+ \beta_{1,8}\mathrm{NV_{it}} \cdot \mathrm{Bad_{it}} \cdot \mathrm{Pre_{it}} + \theta_1 Controls + \varepsilon_{1,it}$$

where *Controls* indicate all other controls in the model and $\varepsilon_{i,it}$ is the error term associated with the model. Among the interaction terms, the coefficient $\beta_{1,5}$ of the product between news valence and a dummy for negative news ($NV_{i,t} \times Bad_{i,t}$) captures the distinct effects of negative versus positive news; in other words, the negativity effect (H_1). Also, the term multiplying news valence by pre-news sentiment ($NV_{i,t} \times Pre_{i,t}$) captures the effect of positive herd behavior and is used to test H_{2a}. Finally, we include one three-way interaction term ($NV_{i,t} \times Bad_{i,t} \times Pre_{i,t}$), which is used to test whether negative pre-news sentiment for a company intensifies the effect of negative news on sentiment change (H_{2b}: negative herding). Also, in conjunction with the two-way interaction term $NV_{i,t} \times Bad_{i,t}$, the term shows how the negativity effect holds in the presence of negative herding.

The full model, Model 2 (equation 5), includes all the terms in the base model (Model 1) and the interaction terms between the main variables and the dummy for B2C to estimate the differences in the effects between B2C and B2B companies. Thus, Model 2 is specified as follows:

$$\text{(5) } \mathrm{SC_{it}} = \alpha_{2t} + \alpha_{2i} + \beta_{2,1}\mathrm{NV_{it}} + \beta_{2,2}\mathrm{Bad_{it}} + \beta_{2,3}\mathrm{Pre_{it}} + \beta_{2,4}\mathrm{B2C_{it}}$$

$$+ \beta_{2,5}\mathrm{NV_{it}} \cdot \mathrm{Bad_{it}} + \beta_{2,6}\mathrm{NV_{it}} \cdot \mathrm{Pre_{it}} + \beta_{2,7}\mathrm{Bad_{it}} \cdot \mathrm{Pre_{it}} + \beta_{2,8}\mathrm{NV_{it}} \cdot \mathrm{Bad_{it}} \cdot \mathrm{Pre_{it}}$$

[6] The subscripts of coefficients are numbered to match the same terms across models. The first indicates model number and the second, the terms.

$$+ \beta_{2,9}\mathrm{NV_{it}} \cdot \mathrm{B2C_{it}} + \beta_{2,10}\mathrm{Bad_{it}} \cdot \mathrm{B2C_{it}} + \beta_{2,11}\mathrm{Pre_{it}} \cdot \mathrm{B2C_{it}}$$

$$+ \beta_{2,12}\mathrm{NV_{it}} \cdot \mathrm{Bad_{it}} \cdot \mathrm{B2C_{it}} + \beta_{2,13}\mathrm{NV_{it}} \cdot \mathrm{Pre_{it}} \cdot \mathrm{B2C_{it}} + \beta_{2,14}\mathrm{Bad_{it}} \cdot \mathrm{Pre_{it}} \cdot \mathrm{B2C_{it}}$$

$$+ \beta_{2,15}\mathrm{NV_{it}} \cdot \mathrm{Bad_{it}} \cdot \mathrm{Pre_{it}} \cdot \mathrm{B2C_{it}} + \theta_2 Controls + \varepsilon_{2,it}$$

where the main effect of B2C ($\beta_{2,4}$) and the interaction effects with B2C ($\beta_{2,9}$–$\beta_{2,15}$) are newly included in addition to the terms in Model 1. In this model, H_3 concerning the B2C and B2B comparison is tested. That is, the coefficient $\beta_{2,5}$ of $NV_{i,t} \times Bad_{i,t}$ captures negativity effect for B2B (when B2C dummy is zero); Positive herding and negative herding for B2B is tested with the coefficients of $NV_{i,t} \times Pre_{i,t}$ and $NV_{i,t} \times Bad_{i,t} \times Pred_{i,t}$ (i.e., $\beta_{2,6}$ and $\beta_{2,8}$). As for the terms including B2C, the coefficients of $NV_{i,t} \times Bad_{i,t}$ and $NV_{i,t} \times Bad_{i,t} \times B2C_{i,t}$ capture whether the negativity effect is greater for B2C companies (H_{3a}). The three-way interaction term $NV_{i,t} \times Pre_{i,t} \times B2C_{i,t}$ and the four-way interaction term $NV_{i,t} \times Bad_{i,t} \times Pre_{i,t} \times B2C_{i,t}$ (along with their B2B baseline terms) test whether positive and negative herding are less for B2C, relevant to H_{3b} and H_{3c}.

Empirical Findings

We first provide the results of the hypothesis testing along with the interpretation of other variables in our models. Next, we present the results of long-term impacts—whether the negativity effect, herd behavior, and the directionality of the herd behavior persist over time. We then add a B2C versus B2B indicator to examine its moderating role. Finally, we suggest an additional analysis to test the proposed mechanism of herd behavior.

[Insert Table 4 about here]

Hypothesis Testing

Table 4 reports the results of our empirical analyses. As described in the Model section, Model 1 is the base model, and Model 2 is the full model, which includes the moderating effects of B2C. As explained above, Model 1 is used in testing H_1 and H_2, and Model 2, H_3.

As for the negativity effect, the coefficient of $NV_{i,t} \times Bad_{i,t}$ for Model 1 is positive and significant ($\beta_{1,5} = .163$, $p < .01$), suggesting an asymmetrical sensitivity of post-news sentiment to news of different valence. That is, the post-news sentiment is more sensitive to negative news than to positive news (H_1 supported).

Regarding the herd behavior, the coefficient of the $NV_{i,t} \times Pre_{i,t}$ is not significant, implying that consumers do not overreact to positive news when pre-news sentiment is positive. We thus conclude that H_{2a} is not supported. On the other hand, the coefficient of $NV_{i,t} \times Bad_{i,t} \times Pre_{i,t}$ is positive and significant ($\beta_{1,8} = .026$, $p < .05$), and its effect size is larger than that of $NV_{i,t} \times Pre_{i,t}$, indicating that herding indeed manifests itself when news valence is negative. Thus, herding happens only when bad news arrives for companies with a negative pre-news sentiment.

Lastly, we test H_{3a} about the difference in negativity effect according to the type of companies (B2C vs. B2B). The coefficient of $NV_{i,t} \times Bad_{i,t} \times B2C_{i,t}$ is positive and significant ($\beta_{2,12} = .071$, $p < .01$), implying that B2C companies encounter stronger negativity bias, thus supporting H_{3a}. When consumers already have some knowledge about the company, they rely more on official news and their judgment, resulting in selective information processing that reinforces the pre-existing sentiment and hence an overreaction to bad news (Facione et al. 1995; Hochbaum 1954; Ahluwalia 2002). Second, H_{3b} and H_{3c} concern the positive and negative herd behavior of B2C vs. B2B companies. We hypothesized that the moderating effect of pre-news sentiments on the relationship between the news and consumer sentiment changes is less for B2C than B2B companies. Thus, herding behavior would be more pronounced for B2B companies than B2C because consumers rely on all information sources, including others' opinions, since they generally lack the knowledge for B2B companies than B2C companies. The coefficient of $NV_{i,t} \times Pre_{i,t} \times B2C_{i,t}$ is not significant, and thus we do not find strong evidence to support H_{3b}. This implies that consumers do not display greater herd behavior for B2C companies. On the other hand, the coefficient of $NV_{i,t} \times Bad_{i,t} \times Pre_{i,t} \times B2C_{i,t}$ is negative and significant ($\beta_{2,15} = -.102$, $p < .01$), indicating that the effect of negative pre-news sentiments on the relationship between the negative news and post-news sentiment change is less for B2C than B2B companies. By comparing the coefficients of $NV_{i,t} \times Bad_{i,t} \times Pre_{i,t}$ and $NV_{i,t} \times Bad_{i,t} \times Pre_{i,t} \times B2C_{i,t}$, we find that negative herding is greater for B2B companies than B2C companies. Thus, hypothesis H_{3c} is supported.

To sum up, consumers overreact to negative news. When there is positive pre-news sentiment for companies, consumers marginally underreact to positive news. When there is negative pre-news sentiment, however, consumers significantly overreact to negative news. Thus, herding manifests only on the negative spectrum. Lastly, the negativity effect is greater for B2C companies, but negative herding is more apparent for B2B companies.

The Long-Term Impact of News on Consumer Sentiment

We test for the endurance of the impact of news and pre-news sentiment on post-news sentiment. By definition, sentiment is persistent (Brown and Cliff 2005) but not necessarily permanent, so we expect the impact of news as a change in sentiment will dissipate over time. However, the degree of brevity or persistence is an empirical question that requires testing. For managers who are dealing with the influence of everyday news publicity, it is important to know whether the impact of a news item likely will be short-lived or is more likely to persist for a long time.

[Insert Table 5 about here]

Table 5 shows the evolution of coefficients for the terms of interest. Time indicates the period corresponding to one day after the news, two days after, and so on, measured as the rolling average. That is, the dependent variable used in each estimation is the difference between seven-day averages of post- and pre-news sentiment. The pre-news sentiment is the average of t – 7 through t – 1 and is kept constant across estimations, while post-news sentiment progresses from t + 1 to t + 7 (time 1), from t + 2 to t + 8 (time 2), and so on.

The coefficients of the $NV_{i,t}$ term capture the impact of news over the following days. The size of the effect decreases and disappears after about 11 days. Negative herding ($NV_{i,t} \times Bad_{i,t} \times Pre_{i,t}$) is also strong and persistent for about 11 days. The effect size decreases gradually, and the impact lasts as long as the news itself. When consumer sentiment is negative toward a company, not only does the bad news create overreaction, but also the negative consumer sentiment lingers. Literature on negativity bias finds that negative information is both more damning and more persistent ("negative dominance," Rozin and Royzman 2001).

Lastly, the coefficients of $NV_{i,t} \times Bad_{i,t} \times Pre_{i,t} \times B2C_{i,t}$ are also persistent. The negative coefficient indicates attenuation of others' opinions for B2C companies. The moderating effect itself disappears after about 20 days, and its duration is more persistent than for B2B companies (about 11 days). This is perhaps due to consumers feeling more knowledgeable about B2C than B2B companies (Glynn 2012; Srinivasan, Lilien, and Sridhar 2011), and thus others' opinion is discounted for a longer period of time. Studies in advertising show that consumers recall new information of familiar brands better than of unknown ones (Kent and Allen 2018), and better recall leads to a prolonged and persistent attitude (Loken and Hoverstad 1985). Applied in our setting, it may be that the memory of news about B2C companies and the accompanying moderating effect linger longer simply because consumers are previously better acquainted with B2C brands.

A Test of Potential Underlying Mechanism for Negative Herding

We purport that one of the potential underlying mechanisms through which negative pre-news sentiment aggravates the consumer reaction to negative news is herd behavior. Herding is a phenomenon in which individuals weigh others' opinions heavily along with their own information and judgment in making a decision (Scharfstein and Stein 1990). Numerous studies in the literature show that herding is stronger when individuals sense greater uncertainty (Sun 2013). This uncertainty can come from outside conditions but also comes from a personal lack of knowledge and experience (Shiu et al. 2011). Thus, the more knowledgeable groups should display less herd behavior than the less knowledgeable groups. If herding were to be the mechanism at work in our context, the better-informed groups should display less overreaction to bad news when pre-news sentiment is negative.

To test whether the herd behavior is one of the underlying mechanisms operating in our context, we run an additional model with a proxy variable indicating the knowledge level of Weibo users and find some indirect evidence for the herd behavior as one of the mechanisms. Specifically, we use *Verified User* (VU) variable, the proportion of Weibos by verified users at the firm-day level, given that the accounts of verified users are typically managed by financial analysts and reporters as described in the Measures section. We utilize Model 1 as the base model and include a new interaction term, $NV_{i,t} \times Bad_{i,t} \times Pre_{i,t} \times VU_{i,t}$. The model result is given in Table 6, and the coefficient of the new interaction term is negative and significant (–0.76, $p < .05$). Thus, a higher ratio of Weibos by verified users negatively moderates the effect of negative news when pre-news sentiment is negative. That individuals with more knowledge and thus less uncertainty show less herding is also consistent with the findings in the literature of herd behavior (Shiu et al. 2011; Sun 2013). We suggest this as evidence for herd behavior being one of the potential mechanisms underlying the phenomena we observe. While not a direct proof as in an experimental setting, it provides a reasonable explanation for the observed overreaction to the negative news in the presence of negative pre-news sentiment.

[Insert Table 6 about here]

The Impact of News and the Role of Pre-News Sentiment on Stock Returns

Previous studies repeatedly find a relationship between consumer sentiment and stock returns (Baker and Wurgler 2006; Bollen, Mao, and Zeng 2011; Deng et al. 2018; Sprenger et al. 2014). Controlling for the fundamentals of a company, consumer sentiment affects abnormal returns in almost all cases. Although the abnormal return is not our main variable of interest, we further investigate the effect of news and pre-news sentiment on abnormal returns to assess the stock market impact of the interplay between the two influencers. Also, we can observe whether the effects manifest differently for post-news sentiment and abnormal returns. We report the impact on the day of the news, one day later, and two days later to see if there are long-term effects also for the return (see Table 7).

The change in stock values in response to the news itself is in line with our intuition. Good news results in higher returns and bad news in lower returns (see the coefficient of the term $NV_{i,t}$). We also observe a negativity effect because the coefficient of the term $NV_{i,t} \times Bad_{i,t}$ is positive and significant. That is, stock returns overreact to negative news. However, we observe herding for the positive pre-news sentiment (see $NV_{i,t} \times Pre_{i,t}$) and attenuating effect for negative ones (see $NV_{i,t} \times Bad_{i,t} \times Pre_{i,t}$).

The primary impact of news is the same for sentiment change and stock returns; however, the secondary effects (i.e., herding, negative herding, and negative herding for B2C companies) are the opposite. We attribute this to the fact that sentiment and abnormal returns are the outcomes of two distinct behaviors: expressions of opinion and investment decisions. The sentiment is driven more by the negative opinions expressed by others, and investment decisions are affected more by the positive opinions expressed by others.

The stock market is biased in a sense. Although anyone can take a positive action —

buying a stock — only those who own stocks can perform the negative action of selling it. We speculate that investors who own stocks may react differently to others' negative opinions, perhaps because stock ownership creates an endowment effect (Kahneman, Knetsch, and Thaler 1990; Morewedge 2016), making them reluctant to sell. Additionally, they may be more optimistic about the stock than others in the market, as made evident by their having bought the stock (Barber and Odean 2008). Thus, the stock market underreacts to negative pre-news sentiment. This is consistent with prior literature that documents stronger positive than negative herding in stock purchasing (Chiang and Zheng 2010; Tan et al. 2008).

[Insert Table 7 about here]

Robustness Checks

We conduct a series of robustness checks to ensure that our findings are not sensitive to our assumptions, construct definitions, and model specifications. Specifically, we test whether observations with neutral news are driving the results, whether the use of company and day fixed effects is too restrictive, and whether a differing number of days for constructing sentiments may change the findings. All analyses are provided and discussed in detail in the Online Appendix.

One possible concern about the data is that most of the company-day observations are neutral. In our sample, more than 90% of company-day observations have neutral (zero) news valance. This is because not all companies appear in the news every day. To address this point, we limit our sample to those company-day observations that contain at least one news item about a specific company. The resulting subsample has company-day observations in which companies are featured in the news in ways other than neutral. We used this alternative dataset to test our models and find that the results are consistent with our hypotheses.

In all our models, we include company and day fixed effects. We test whether our results are sensitive to the model specification by excluding company fixed effects and including various company-level controls. Also, we test the model without day fixed effects and include various market-level factors following the Fama-French-Carhart four-factor model (Carhart 1997).[7] The result shows that our main findings remain qualitatively unchanged.

Finally, the seven-day window used to construct the sentiment measures can be driving the results. Using an average sentiment of several days reduces the daily random fluctuations and better captures the underlying sentiment; however, the exact width of this window may be questionable. To test the sensitivity of the result to the number of days, we construct four sets of pre- and post-news sentiments using three-day, five-day, seven-day and ten-day averages. Using these new sentiment constructs, we test our models and find that the estimation results remain consistent. All robustness test results are given in the Appendix.

Discussion and Conclusion

Understanding consumer sentiment toward a company is critical for managing company value in today's dynamic market environment in which consumers are constantly bombarded with information. Previous studies have focused on how to use consumer sentiment to predict other variables of interest, such as stock returns (Mian and Sankaraguruswamy 2012) or household consumption (Carroll, Fuhrer, and Wilcox 1994). However, little investigation has been done on how this sentiment is formed, especially at the company level. Our study addresses this topic of the determinants of consumer sentiment in the context of news and

[7] The factors included are: (1) RMRF: market portfolio return in excess of the risk-free rate on day *t*, (2) SMB: return on a portfolio of small stocks minus large stocks on day *t*, (3) HML: return on a portfolio of long high book-to-market stocks and short low book-to-market stocks on day *t*, (4) MOM: return difference between stocks with a high and low past return at day *t*.

pre-existing sentiment.

We find that news about companies does affect consumer sentiment in a systematic and expected fashion. Positive news leads to a positive change in consumer sentiment, and negative news leads to a negative change. However, consumers overreact under certain conditions. When news is negative, consumers overreact. As for pre-news sentiment, negative sentiment results in overreaction to negative news.

We attribute the negative overreaction in the presence of negative pre-news sentiment as the result of herd behavior. That is, consumers observe and imitate others when forming opinions based on new information. We test this supposition by investigating the moderating role of the proportion of expert sentiment. We find that the higher the experts in the opinion pool, the lesser the negative overreaction in the presence of negative sentiment. We suggest this result as one evidence that herding is one of the underlying mechanisms that drive the phenomena in our context.

Negativity bias and herding are moderated by the type of company whose news is released. B2C companies often interact directly with consumers through marketing communication and retail touchpoints. Consumers have a sense of intimacy and confidence in "knowing" the company, whether this familiarity is well-grounded or illusive. Because of this predisposition, consumers trust their own judgment more when exposed to official news. This may lead to negativity bias, again because the market is full of companies with positive consumer sentiment. Consumers tend to be affected less by pre-news sentiment when B2C companies are involved, but herd behavior is pronounced with B2B companies, especially when the news is bad. Consumers consider all information sources, including others' pre-existing opinions, when they are not familiar with the companies involved (i.e., B2B).

Negative herding has a long-term impact. The news effect on consumer sentiment itself lingers for about 11 days, be it positive or negative. The effect of negative herding, in general, persists for 11 days, as with the news itself. In sum, we conclude that negative herding is significant, enduring, and thus a consistent market phenomenon that needs to be heeded by academics and managers alike.

The impact of news and the role of the pre-news sentiment on stock returns is not the same as on post-news sentiment. The main effect of the official news on stock returns is as expected: Positive news increases abnormal returns and vice versa, but negative news has a greater impact (negativity bias). However, herding is observed for positive news and not for negative news. These findings are the opposite of what we observe for sentiment changes. We attribute this reversal of the moderating effects to the distinctness of the actions that lead to post-news sentiment and abnormal returns. The former is an expression of opinion, but the latter is an investment decision.

It is apparent that in our setting, negative pre-news sentiment plays a greater role when expressing an opinion, but positive pre-news sentiment drives investment decisions. We explain that the overreaction to the opinion of others in the domain of sentiments is because negative information is more diagnostic and newsworthy among a deluge of good financial news. The underreaction to a negative opinion of others in the stock market can be because of the unique bias that stockholders have. That is, owners of a specific stock may value it more than is warranted by the observed fundamentals of the company.

Contributions and Implications for Managers

Our main contribution is that we address the changes in consumer sentiment at the company level. Most of the studies on consumer sentiment focus on using it to predict or explain other outcomes such as stock price sensitivity (Mian and Sankaraguruswamy 2012) or sales (Sonnier, Mcalister, and Rutz 2011). To our knowledge, our work is the first to systematically investigate how consumer sentiment toward companies evolves in the face of such market forces.

In addition, we find and verify a robust phenomenon that has not been widely recognized, namely negative herding. Despite numerous studies on the negativity effect and still more on herd behavior, few have examined their interplay (see Table 1). A handful of studies that did examine do not agree on their findings. We establish that there is a negative overreaction to bad news only in the presence of previously negative sentiment. We also compare the changes in consumer sentiment (e.g., negativity effect, herd behavior, and negative herding) between B2C and B2B companies, a difference unexplored in the previous literature. With the recent deluge of studies on the role of social media for B2B companies (see, e.g., Swani, Brown, and Milne 2014 and Buratti, Parola, and Satta 2018), our finding that pre-news sentiment plays a greater role in the context of B2B is a valuable addition to the field.

Another contribution of this work is the use of a novel and extensive dataset that contributes substantially to the empirical body of evidence in the study of consumer sentiment and herd behavior. We use the entire population of Weibos and news articles in the Chinese market for an observation period of two years. We combine this data with the population of all listed companies in China, along with publicly available data such as stock prices and total assets. The empirical evidence we provide is thus robust.

We also provide evidence that the driving mechanism behind the negative overreaction to negative news in the presence of negative sentiment is due to herd behavior. Studies on herd behavior often observe the outcome and conjecture why such behavior is observed theoretically but seldom test the mechanism empirically. Ours is a rare exception in which we provide empirical evidence based on an extensive dataset over a prolonged time period.

Our study is especially applicable to sentiment studies in finance, suggesting ways to reduce uncertainty and seemingly high volatility in the stock market. It is a tradition in finance to view sentiment and emotion as “noise” or irrationality that has little to do with fundamentals (Baker and Wurgler 2007). As this irrationality has a predictable pattern that can be explained by observable market forces, consumer sentiment can be viewed as company assets, much like brand equity (Simon and Sullivan 1993). Consumer sentiment is enduring (Cattell 1940; Munezero et al. 2015) and can predict company performance (Chen et al. 2014; Subrahmanian and Kumar 2017). As such, understanding how this sentiment develops can help managers and investors better evaluate company value. Our findings can give managers substantial insights and suggestions for actionable plans to manage relatively frequent publicity crises and opportunities. Good and bad news have an impact. However, consumer reactions differ greatly depending on the direction of pre-existing sentiment. Negative pre-news sentiment creates an overreaction to bad news. In this unfortunate scenario, the damage to future sentiment is grave and also persistent. Thus, the most important precautionary measure to take is to maintain awareness of consumer sentiment toward the company as part of its regular status assessment. If this sentiment is negative, its cause needs to be identified and remedied as soon as possible before the problem is compounded by the arrival of unexpected and unforeseeable bad news. As Wies et al. (2019) demonstrate, when stakeholders are disgruntled, advertising investment to address their complaints can be not only effective but crucial in protecting firm value.

Further Research

Future studies in several directions can improve upon aspects of our study. First, the microblogging data we obtained are not individual-level data because we cannot identify which Weibos were tweeted by the same person. The power law often observed in the sphere of Internet usage predicts that a few people will tweet excessively and many people will tweet a few times (Adamic and Huberman 2000). If sentiment changes to a more extreme end of the spectrum — for instance, more toward the negative — it is not clear whether this is due to more people tweeting negatively or previously negative persons tweeting excessively. However, when we observe changes in sentiment, the additional negative tweets could not have all come from the previously negative consumers. In fact, the aforementioned power law predicts that the additional negative tweets that intensified overall sentiment more negatively would have come from a few consumers who tweet heavily and from many users who tweet lightly. In other words, it is safe to assume that when the sentiment turns negative, many consumers will, in fact, also turn negative.

Another caveat of not having individual identifiers is that it is hard to show the mechanism behind the phenomena. We cannot suggest definitive evidence that herding is the dominating mechanism that drives the result and categorically rule out other potential drivers. For instance, it can be observational learning (Zhang 2010), confirmation bias (Yin, Mitra, and Zhang 2016), or other psychological processes. Future studies can use individual-level data to definitively identify mechanisms behind the observed phenomena and uncover other potential drivers.

An improvement that future studies can make is to use data from various sources since we use the data from a single market, China. While data being from a single country will not compromise the core insight of the study,[8] it may be interesting to conduct a cross-cultural investigation. Similarly, Weibos are the only source used to measure consumer sentiment. Although it is a popular measure for sentiment, there can be noises (e.g., Weibos by the company itself to influence public opinion). Future studies can use two or more sources of consumer sentiment as done by Brown and Cliff (2004) to "triangulate" the true underlying sentiment and test whether negative herding can still be observed.

[8] Although the Chinese market has its distinctiveness, there is no reason to believe Chinese investors will react to news or social media any differently than those in other countries (Ren et al. 2021).

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TABLE 1
Academic Evidence of Herd Behavior and its Direction

Study	Literature	Domain	Negativity	Positivity
Nadeau, Cloutier, and Guay (1993)	Bandwagon	Opinion on issues	✓	✓
Valdés (2000)	Contagion	Financial markets	✓	✓
Walter and Moritz Weber (2006)	Herd behavior	Mutual funds	✓	✓
Muchnik, Aral, and Taylor (2013)	Herd behavior	Comment voting	✓	✓
Chiang and Zheng (2010)	Herd behavior	Stock market	✓	✓
Choi, Dassiou, and Gettings (2000)	Herd behavior	Online product choice	✓	✓
Clement and Tse (2005)	Herd behavior	Financial analysts	✓	✓
Duan, Gu, and Whinston (2009)	Informational cascade	Software adoption	✓	✓
Lee, Hosanagar, and Tan (2015)	Informational cascade	Online movie rating	✓	✓
Marsh (1985)	Bandwagon	Opinion on issues	✓	✓
Tan et al. (2008)	Herd behavior	Stock market	✓	✓
Chen (1999)	Information externality	Bank runs	✓	
Zhang, Craciun, and Shin (2010)	Observational learning	Organ transplant	✓	
Zhou and Sornette (2006)	Herd behavior	Stock market	✓	
Barsade (2002)	Contagion	Social interactions		✓
Biddle (1991)	Bandwagon	Adoption of vanity plates		✓
Cai, Chen, and Fang (2009)	Observational learning	Food choice		✓
Chen (2008)	Herd behavior	Online product choice		✓
Hanson and Putler (1996)	Herd behavior	Online product choice		✓
Herzenstein, Dholakia, and Andrews (2011)	Herd behavior	P2P loan auction		✓
Huang and Chen (2006)	Herd behavior	Online product choice		✓
Kiss and Simonovits (2014)	Bandwagon	Election voting		✓
Moe and Schweidel (2013)	Bandwagon	Online reviews		✓
Sun (2013)	Herd behavior	Technology adoption		✓

TABLE 2

Variable Definitions

Variable	Description
Key variables	
$Pre_{i,t}$	Prenews sentiment for company i on day t measured as the average sentiment from t – 7 to t – 1
$Post_{i,t}$	Postnews sentiment for company i on day t measured as the average sentiment from t + 1 to t + 7
$SC_{i,t}$	Sentiment change for company i on day t (= $Post_{i,t}$ – $Pre_{i,t}$)
$NV_{i,t}$	Valence of news on company i on day t
$Bad_{i,t}$	Indicator of whether the news valence is below zero (1 = below zero, 0 = otherwise)
$B2C_i$	Indicator of whether the majority of company revenue comes from business-to-consumer transactions (1 = B2C, 0 = B2B)
$VU_{i,t}$	The proportion of Weibos tweeted by verified users for company i on day t
Control variables	
$Size_{i,t}$	One-day lagged natural logarithm of one plus the product of the number of outstanding shares and the closing price of the stock
$P/B_{i,t}$	One-day lagged natural logarithm of one plus the price-to-book ratio
$Cret_{i,t}$	Cumulative return over the past week

TABLE 3

Summary Statistics

	Centiles						
Variable	1%	10%	50%	90%	99%	Mean	SD
$Pre_{i,t}$	–.400	.000	.856	1.787	2.804	.894	.725
$Post_{i,t}$	–.400	.000	.911	1.809	2.809	.897	.726
$SC_{i,t}$	–1.644	–.747	.000	.751	1.688	.003	.631
$NV_{i,t}$	–.693	.000	.000	.000	1.386	.060	.294
$Bad_{i,t}$	0	0	0	0	1	.019	.136
$B2C_{i}$	0	0	0	1	1	.234	.423
$VU_{i,t}$	–2.432	–.802	.000	.738	1.190	.000	.686
$Size_{i,t}$	20.750	21.220	22.101	23.539	25.304	22.270	.955
$P/B_{i,t}$	.548	.815	1.270	2.016	3.872	1.384	.618
$Cret_{i,t}$	–.131	–.061	.005	.077	.196	.008	.063

Note: Sample size is 1,737,942. $VU_{i,t}$ is mean-centered.

TABLE 4

Estimation Results

	Model 1		Model 2 (Full Model)	
	Est.	SE	Est.	SE
Main Variables				
$NV_{i,t} \times Bad_{i,t}$	.163*	.013	.126**	.017
$NV_{i,t} \times Pre_{i,t}$	–.003	.002	–.006**	.002
$NV_{i,t} \times Bad_{i,t} \times Pre_{i,t}$	.026*	.011	.070**	.014
$NV_{i,t} \times Bad_{i,t} \times B2C_{i}$			.071**	.027
$NV_{i,t} \times Pre_{i,t} \times B2C_{i}$			.007	.004
$NV_{i,t} \times Bad_{i,t} \times Pre_{i,t} \times B2C_{i}$			–.102**	.022
Control Variables				
$NV_{i,t}$	.080**	.002	.092**	.003
$Bad_{i,t}$	.052**	.011	.035*	.014
$Pre_{i,t}$	–.638**	.001	–.640**	.001
$Bad_{i,t} \times Pre_{i,t}$	.026**	.009	.050*	.012
$NV_{i,t} \times B2C_{i}$			–.036**	.005
$Bad_{i,t} \times B2C_{i}$			.022	.023
$Pre_{i,t} \times B2C_{i}$			.010**	.001
$Bad_{i,t} \times Pre_{i,t} \times B2C_{i}$			–.049**	.019
$Size_{i,t}$	.124**	.002	.124**	.002
$P/B_{i,t}$	–.086*	.002	–.086**	.002
$Cret_{i,t}$	–.050**	.007	–.049**	.007
Adjusted R-squared	.4077		.4078	

Note: Day and company fixed effects are included in all models, but their estimates are omitted for brevity.
* and ** indicate significance at $p < .05$ and $p < .01$, respectively.

TABLE 5

The Long-Term Impact of News and Pre-news Sentiment on Post-news Sentiment

Time after news[a]	$NV_{i,t}$		$NV_{i,t} \times Bad_{i,t} \times Pre_{i,t}$		$NV_{i,t} \times Bad_{i,t} \times Pre_{i,t} \times B2C_i$	
	Est.	SE	Est.	SE	Est.	SE
1	.092**	.003	.070**	.015	–.102**	.022
2	.052**	.011	.065**	.015	–.124**	.022
3	.039**	.011	.062**	.015	–.139**	.022
4	.029**	.011	.057**	.015	–.136**	.022
5	.025**	.011	.058**	.015	–.139**	.022
6	.021**	.011	.062**	.015	–.132**	.022
7	.017**	.012	.056**	.015	–.118**	.023
8	.015**	.012	.047**	.015	–.102**	.023
9	.012**	.012	.042**	.015	–.090**	.023
10	.010**	.012	.040**	.015	–.074**	.023
11	.007*	.012	.036*	.015	–.076**	.023
12	.004	.012	.029	.015	–.081**	.023
13	.002	.012	.024	.015	–.055*	.023
14	.000	.012	.003	.015	–.059*	.023
15	.000	.013	.002	.015	–.055*	.023
16	.001	.013	.004	.016	–.049*	.023
17	.001	.003	.001	.016	–.049**	.023
18	.001	.003	–.007	.016	–.045*	.023
19	.003	.003	–.003	.016	–.042*	.023
20	.005	.003	.000	.016	–.024	.023

Note: [a] Time is the rolling average of seven days, starting from t+1 for time 1.
Day and company fixed effects are included in all models. * and ** indicate significance at $p < .05$ and $p < .01$, respectively.

TABLE 6

Test of the Potential Mechanism: Verified User as a Moderator

	Model 1	
	Est.	SE
Main Variables		
$NV_{i,t} \times Bad_{i,t}$	.197**	.014
$NV_{i,t} \times Pre_{i,t}$	–.002**	.002
$NV_{i,t} \times Bad_{i,t} \times Pre_{i,t}$	.003**	.013
$NV_{i,t} \times Bad_{i,t} \times Pre_{i,t} \times VU_{i,t}$	–.076**	.012
Control Variables		
$NV_{i,t}$	.076**	.002
$Bad_{i,t}$	.086*	.012
$Pre_{i,t}$	–.662**	.001
$VU_{i,t}$	–.004**	.001
$Bad_{i,t} \times Pre_{i,t}$	–.006	.011
$NV_{i,t} \times VU_{i,t}$	–.024**	.003
$Bad_{i,t} \times VU_{i,t}$	.120**	.013
$Pre_{i,t} \times VU_{i,t}$	–.052**	.001
$Bad_{i,t} \times Pre_{i,t} \times VU_{i,t}$	–.074**	.010
$Size_{i,t}$	.110**	.002
$P/B_{i,t}$	–.085**	.002
$Cret_{i,t}$	–.116**	.007
Adjusted R-squared		.4129

TABLE 7

The Impact of News on Stock Returns and the Role of Pre-news Sentiment

	Day of News		One Day Later		Two Days Later	
	Est.	SE	Est.	SE	Est.	SE
$NV_{i,t}$	.648**	.016	.366**	.018	.038	.021
$Bad_{i,t}$	.515**	.081	.188*	.091	.051	.107
$Pre_{i,t}$	–.050**	.005	–.113**	.006	–.091**	.007
$NV_{i,t} \times Bad_{i,t}$	.324**	.093	.189	.106	.104	.123
$NV_{i,t} \times Pre_{i,t}$	.248**	.012	–.012	.013	.021	.015
$Bad_{i,t} \times Pre_{i,t}$	–.453**	.066	–.096	.076	–.180*	.089
$NV_{i,t} \times Bad_{i,t} \times Pre_{i,t}$	–.550**	.077	–.120	.089	–.222*	.103
$NV_{i,t} \times B2C_i$	–.231**	.028	–.233**	.031	.011	.037
$Bad_{i,t} \times B2C_i$	–.238	.137	–.010	.153	–.035	.177
$Pre_{i,t} \times B2C_i$	.035**	.009	.021*	.010	–.005	.011
$NV_{i,t} \times Bad_{i,t} \times B2C_i$	–.099	.157	.141	.176	–.049	.202
$NV_{i,t} \times Pre_{i,t} \times B2C_i$	–.098**	.019	.095**	.022	.023	.026
$Bad_{i,t} \times Pre_{i,t} \times B2C_i$	.260*	.109	–.172	.121	.071	.142
$NV_{i,t} \times Bad_{i,t} \times Pre_{i,t} \times B2C_i$	260*	.126	–.304*	.141	–.039	.164
Observations		1,106,276		866,897		634,475
Adjusted R-squared		0.2653		0.2227		0.2013

Note: Day and company fixed effects are included in all models. * and ** indicate significance at $p < .05$ and $p < .01$, respectively.

FIGURE 1

The Conceptual Framework