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Sentiment stocks

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ABSTRACT

To study how investor sentiment at the firm level affects stock returns, we match more than 58 million social media messages in China with listed firms and construct a measure of individual stock sentiment based on the tone of those messages. We document that positive investor sentiment predicts higher stock risk-adjusted returns in the very short term followed by price reversals. This association between stock sentiment and stock returns is not explained by observable stock characteristics, unobservable time-invariant characteristics, market-wide sentiment, overreaction to news, or changing investor attention. Consistent with theories of investor sentiment, we find that the link between sentiment and stock returns is mainly driven by positive sentiment and non-professional investors. Finally, exploiting a unique feature of the Chinese stock market, we are able to isolate the causal effect of sentiment on stock returns from confounding factors.

1. Introduction

Seminal theoretical work demonstrates that the erroneous beliefs of noise traders can affect financial asset prices when arbitrageurs face arbitrage risk or when their clients may force them to liquidate positions early at a loss (De Long, Shleifer, Summers, & Waldmann, 1990; Shleifer & Vishny, 1997). Barberis, Shleifer, and Vishny (1998) investigate how investors' wrong expectations are formed and how such expectations can, in turn, explain some puzzling patterns in stock price data such as underreaction and overreaction. There is indeed ample empirical evidence that investor sentiment, defined as investor beliefs about stock value not justified by fundamentals, influences stock prices.[1] While earlier studies focus on market-wide measures of sentiment, the richness of data brought about by the popularity of social media now enables researchers to construct measures of sentiment at the individual stock level. In this paper, we exploit data from 58 million messages posted on one of the world's largest microblogging sites to investigate investor sentiment at the stock level and its impact on stock prices.

Investor sentiment may vary across stocks because some stocks are more likely to be affected by fluctuations in market-wide sentiment than others, as documented by Baker and Wurgler (2006). But investors may also form wrong beliefs about specific firms or industries, regardless of whether their beliefs about the whole market are correct. Put differently, sentiment could affect individual stock prices even in times of neutral sentiment about the whole market. For a recent example, consider the exorbitant but short-lived jumps in prices of stocks of firms adding “blockchain” to their name.[2] Consequently, being able to identify sentiment for individual companies can help active investors predict and exploit differences in abnormal returns across stocks.

The possibility that sentiment affects individual stocks raises two important questions. First, does stock-level sentiment predict stock returns above and beyond market-wide sentiment? To answer this question, we need a measure of stock sentiment at the individual firm level. While market-wide sentiment can be measured using surveys and aggregate market variables (e.g., closed-end fund discount, number of IPOs, equity share in new issues), such measures are not feasible for individual stocks. Second, provided that an individual stock-level sentiment measure is available, does such measure really capture sentiment or does it simply reflect changes in firm-specific fundamentals or

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[1] See, for example, Hirshleifer and Shumway (2003); Baker and Wurgler (2006); Edmans, Garcia, and Norli (2007); Hwang (2011); Stambaugh et al. (2012); Karabulut (2013); García (2013); Da et al. (2015); Huang et al. (2015); Sibley, Wang, Xing, and Zhang (2016); Renault (2017); Xu, Liu, Zhao, & Su, 2017; Marsh and Liu (2018); Hirshleifer et al. (2018).

[2] “Long Island Iced Tea's blockchain pivot is the height of mania,” Financial Times, December 22, 2017

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other confounding factors? While a number of exogenous sources of variation in market-wide investor mood have been proposed in the literature, it is a challenge to find variation in investor sentiment at the individual firm level that is orthogonal to fundamentals.[3]

To address these questions, we infer sentiment at the stock level from a unique data set of posts in China's Sina Weibo during the full 2013–2014 period. Sina Weibo is a Chinese microblogging site with features that are very similar to Twitter, and is one of the largest social media platforms in the world. At the time of our sample period, the market share of Sina Weibo in China was 80%, with over 500 million registered users and 175.7 million monthly active users.[4] In comparison, Twitter had 63 million monthly active users in the US.[5] In February 2017, Weibo surpassed Twitter in terms of market capitalization.[6]

The Chinese market is particularly interesting for the purpose of studying stock-level sentiment for several reasons. First, unlike the US market, retail investors account for a majority of trading activity in the stock exchange. At the end of our sample period, 2014, 85.37% of trading volume corresponded to trades of individual investors.[7] To the extent that retail investors are more prone to investor sentiment, we expect measures of sentiment to be strongly associated with stock returns. Second, users in China may refer to firms' stocks by their ticker and by a short name known as *Jiancheng* that unambiguously refers to the company. In particular, Sina Weibo uses the firm's *Jiancheng* combined with its ticker to identify a stock. For example, "$PetroChina sh601857$" is used to identify PetroChina, the largest listed company in the Chinese market. This is an important feature not shared by other markets, and it enables us to perfectly match Weibo posts to stocks even if the post does not include a ticker. More specifically, we are able to match 58 million Weibo posts in the 2013–2014 period to 2526 different stocks. Sina Weibo also provides us with the tone of each Weibo post (positive/negative/neutral) based on a proprietary dictionary. Using that information, we construct a measure of sentiment at the stock-day level based on the prevalence of positive posts over negative posts for a given stock on a given day.

We start by investigating whether our measure of sentiment predicts future abnormal returns. We find that days of high investor sentiment are followed by significantly high abnormal returns. More specifically, a one standard-deviation increase in sentiment at the stock level predicts an abnormal return between 3.8 and 8.1 basis points (bp) higher than average on the following day, depending on the model specification. Consistent with the notion that such an increase in price is driven by sentiment and not by a change in fundamentals, high abnormal returns are followed by price reversals on the subsequent days. The result is robust to several alternative specifications that account for stock time-varying and time-invariant characteristics. Importantly, it is also robust to the presence of time fixed effects, which confirms the idea that sentiment varies in the cross-section, and not just in the time-series. Therefore, stock-level sentiment, as inferred from social media posts, appears to predict future returns above and beyond market-wide sentiment.

An alternative explanation to our findings is that social media activity reflects news about firm fundamentals and investors overreact to news. If that were the case, we would also observe price increases following a positive tone in social media posts that revert over time. Fortunately, Sina Weibo also provides the tone of news published by virtually all Chinese media using the same dictionary and matched to stocks through both the tickers and *Jiancheng* names. Including a measure analogous to investor sentiment based on firm news published in the media as a regressor, does not change our results with respect to the link between investor sentiment and stock returns. Therefore, our results do not appear to be driven by overreaction to news.

An important strand of the financial literature posits that investor attention is a scarce resource and investigates the consequences of inattention on financial decisions and market outcomes (Hirshleifer, Lim, & Teoh, 2009; Peress & Schmidt, 2020). According to this literature, increases in investor attention predict higher stock prices followed by price reversals in the long term (Barber & Odean, 2008; Da, Engelberg, & Gao, 2011). The reason is that increases in attention lead to net purchases by retail investors, since the number of stocks that an individual investor can buy–the universe of listed stocks–is much larger than the number of stocks an individual investor can sell without short sales–those already in the investor's portfolio. Although it is unclear why that would be the case, we cannot discard that our measure of sentiment is positively correlated with investor attention. To distinguish between the two competing hypothesis, we construct a direct measure of attention, the total number of posts associated with a particular firm on a given day, and include this measure as a control in our tests. Consistent with the attention literature, we find that our measure of attention has a strong predictive power with respect to stock returns. However, including attention in the regression does not alter our conclusions with respect to sentiment.

Following Antweiler and Frank (2004) and Leung and Ton (2015), we investigate the relationship between sentiment and stock return volatility. We find that controlling for volatility in the recent weeks does not alter our conclusions regarding the relationship between sentiment and stock returns. However, we find that a week of high sentiment is weakly associated with higher volatility over the next two weeks.

We then test other implications of the the sentiment hypothesis. First, following Barber and Odean (2008), we expect positive and negative sentiment to impact stock prices differently. Similarly to the argument for the effect of attention on stock prices, this asymmetry arises because investors can purchase any stock whereas sales are restricted to the stocks they own (without recurring to short sales). Consistent with this hypothesis, we find that only the number of positive posts predicts stock returns.

Second, building on De Long et al. (1990) and Barber and Odean (2008), we hypothesize that retail investors are more likely to be prone to sentiment than professional investors. Therefore, if posts by professional investors have any impact of stock returns, we expect that impact to be permanent, as their posts are likely to convey fundamental information or analysis not available elsewhere. Fortunately, a unique feature of our data allows us to test this hypothesis. More specifically, Weibo distinguishes between two types of users: verified users and non-verified users. Verified users are mainly professional investors in the stock market (mutual fund managers, financial analysts, and finance professionals in general) and non-verified users are mostly retail investors. Consistent with our hypothesis, we find that the positive tone of professional investors' posts is associated with a positive and permanent increase in stock prices.

Finally, while fixed effects and controls are useful to account for *some* potential confounding factors, we cannot safely claim that sentiment captured by social media posts has a causal effect on stock returns based only on our results. To isolate the impact of sentiment on stock returns from other potential factors affecting prices, we would need to observe variation in sentiment that is orthogonal to other stock price determinants. Luckily, a feature of the Chinese market enables us to perform this analysis. More specifically, the Chinese market supervisor mandates stock delisting risk warning announcements for firms whose risk of delisting from the exchange has been previously announced to the public. Such announcements are just an automatic reminder to

[3] Examples of studies using exogenous measures of market-wide investor sentiment include: Hirshleifer and Shumway (2003) (weather); Kamstra, Kramer, and Levi (2003) (seasonal affective disorder), and Edmans et al. (2007) (national sports events).

[4] 2014 Sina annual financial report and Weibo Market, CNNIC, Feb 13, 2015 (in Chinese).

[5] 2014 Twitter Annual Report.

[6] "China's Weibo Is Now Worth More Than Twitter," Bloomberg, Feb 12, 2017.

[7] 2014 Annual Report, China Securities Regulatory Commission.

investors and therefore, they do not contain any new information. Instrumenting our measure of sentiment with the stock delisting announcement, we find evidence of a causal effect of sentiment on stock returns.

Taken together, our empirical results provide strong support for the hypothesis that investor sentiment, as inferred from the activity of individuals interacting on social media platforms, drives stock returns at the individual firm level. Moreover, this effect on stock returns is distinct from that of news or attention, is asymmetric, and is mainly driven by retail investors.

Our paper belongs to an active and growing literature investigating the role of investor sentiment in financial markets (Baker & Wurgler, 2006; Baker, Wurgler, & Yuan, 2012; Deng, Huang, Sinha, & Zhao, 2018; Hirshleifer, Jian, & Zhang, 2018; Huang, Jiang, Tu, & Zhou, 2015; Ranco, Aleksovski, Caldarelli, Grčar, & Mozetič, 2015; Renault, 2017; You, Guo, & Peng, 2017). We study the impact of firm-level sentiment on stock returns in an important and still underexplored market, China, characterized by widespread adoption of social media as well as large retail investor participation in the stock market. Both features make it a particularly appropriate laboratory to study investor sentiment. While other authors have used social media microblogging to investigate investor sentiment in Chinese stocks markets (Guo, Sun, & Qian, 2017; Xu, Liu, Zhao, & Su, 2017), those studies focus on market-wide sentiment, rather than sentiment at the firm level.

Compared to studies of individual-stock sentiment for US markets (Antweiler & Frank, 2004; Sprenger, Tumasjan, Sandner, & Welpe, 2014), our sample is substantially larger and also more representative of the whole market, since stocks included in previous studies tend to be firms with large market capitalization and liquidity given that they are index constituents.

Leung and Ton (2015) study the impact of messages posted on the largest Australian stock message board in a sample covering more than 2000 stocks. They find that the number and bullishness of the messages are positively associated with contemporaneous returns of small growth stocks, but do not predict future returns. These findings suggest that specialized social media can be used for the effective and rapid dissemination of private information in stocks that receive less media attention. Our results complement theirs by showing that in addition to being a channel for the dissemination of legitimate information, social media can also propagate sentiment, and therefore contribute to prices diverging from fundamentals. The conditions under which social media enhance or hamper market efficiency is an important question that we leave for future research.

Moreover, we extend the literature on firm-level sentiment in several important directions. First, we are the first to distinguish between social media sentiment and news sentiment at the firm level, which enables us to discard the alternative explanation that social media conversations simply reflect news and investors overreact to news. Rognone, Hyde, & Zhang, 2020 study the impact of news sentiment on Bitcoin and other currencies. More closely related to our work, Gan, Alexeev, Bird, and Yeung (2020) study the separate effect of news sentiment and social media sentiment at the broad stock market level using US data. Second, we distinguish for the first time between different types of social media users, characterized by different levels of sophistication. Our results suggest that this distinction is important and necessary. Third, we propose a new measure of attention based on the volume of social media conversations about a stock and show that both attention and sentiment impact stock returns independently. Wen, Xu, Ouyang, and Kou (2019) have recently proposed search frequency from the Baidu Index as a measure of investor attention to individual stocks in China. Finally, we identify the causal relationship between investor sentiment and stock returns at the firm level. Previous studies provide evidence that investor sentiment, proxied by social media, is associated with stock returns. Our paper uses stale announcements as an instrument for attention that allows for a causal interpretation of this relationship.

2. Data

2.1. Stock-level investor sentiment

As explained in the introduction, we construct a proxy for investor sentiment with respect to individual stocks using proprietary data from the Chinese social media website Sina Weibo.

Sina first extracts all the Weibo posts that mention a Chinese stock by using the ticker and *Jiancheng*, short name in Chinese, during the full 2013–2014 period. Sina also provides us with the tone of each Weibo post (positive/negative/neutral). In particular, the company uses a dictionary-based automatic textual analysis in a similar fashion to other sentiment databases, such as Thomas Reuter Sentiment Index. The company first assigns each word in a post a score according to their proprietary dictionary. Depending on the sum of all scores of words that are contained in one post, the tone of this post is defined as positive, negative, or neutral.

An important concern is whether the tone data obtained from Sina is reliable. Similarly to other commercial sentiment databases (e.g., Thompson Reuters MarketPsych Index database), Sina does not reveal their proprietary dictionary to the public. However, we believe this measure is reliable for two reasons. First, the dataset is currently used by many practitioners. Another comparable dataset offered by Sina has been adopted and used to edit the Big Data Series Indices by the Shenzhen Stock Exchange.[8] Our dataset follows the same method as the dataset used by the Shenzhen Stock Exchange. Through public information, we also confirm that as of the end of July 2016, at least three mutual funds (Nanfang Big Data 100, Nanfang Big Data 300, and Dongxin Zhongzhi Youxuan) explicitly claimed that they manage assets based on the information from the Sina sentiment database.

Second, we verify the proprietary sentiment dictionary used by Sina using a third party commercial software. Although we cannot match Weibo post sentiment and Weibo post content, Sina provides news items and their tones. Specifically, we randomly select 40,000 news items from December 2014. We use a third-party commercial software, *BosonNLP*, to calibrate the tones of these news items and compare them with the sentiment provided by Sina.[9] We find that 82.67% of the sample provided by Sina has the same sentiment as that determined by the third-party software.

The data set covers all Weibo posts that mention a firm's stock, each post's time stamp, and its tone, as provided by Sina, during the full 2013–2014 period. The original dataset includes around 58 million stock-related Weibo posts. For each stock and each day, we count the number of positive, negative, and neutral Weibo posts. Our panel has more than 1436 million stock-day observations, covering 2526 unique stocks. On average, every stock has 41.34 Weibo posts per day.

Using the tone of each Weibo post, we compute a measure of individual stock sentiment adapted from Antweiler and Frank (2004). More specifically, for each stock i and day t, we count the number of posts with a positive, neutral, and negative tone, which we denote by $p_{i,t}$, $z_{i,t}$ and $n_{i,t}$, respectively. We then construct a measure of positive sentiment as follows:

$$S_{i,t} = ln\left(\frac{1 + p_{i,t}}{1 + n_{i,t}}\right). \tag{1}$$

We propose a new proxy for investor attention to a given stock based on the total number of posts related to that stock. More specifically, we compute our measure of attention for stock i on day t as follows:

$$Attention_{i,t} = ln(1 + p_{i,t} + z_{i,t} + n_{i,t}) \tag{2}$$

[8] http://www.szse.cn/main/disclosure/bsgg_front/39752840.shtml (in Chinese).

[9] Zheng, Wang, Sun, Zhang, and Kahn (2019) use *BosonNLP* to verify the validity of Sina Weibo's sentiment, which they use to measure individuals' happiness.

2.2. News data

We obtain stock-specific news data from Sina News, one of the most important news aggregators in China. Using the same proprietary sentiment dictionary and the same method as that employed with Weibo posts, Sina calibrates the tone of stock-related news. Using the number of news items with positive and negative tone, we calculate stock news sentiment for each stock i and day t, $NS_{i,\ t}$, analogously to Eq. (1).[10]

2.3. Data on stock characteristics

We obtain stock market data from Resset, a commonly used academic database for the Chinese stock market (see, e.g., Fonseka, Samarakoon, & Tian, 2012, and Li, Song, & Wu, 2015). In particular, we have data on firm market capitalization, price-to-book (PB) ratio, turnover ratio, and trading volume.

We obtain daily data on the three Fama-French factors and momentum from the same database (Carhart, 1997; Fama & French, 1993). For each quarter, we first regress daily excess returns on the factors. We then calculate the daily abnormal return, $\alpha_{i,\ t}$, as the excess daily return of stock i on day t minus the product of the estimated factor loadings from the previous quarter and the stock's factor realization on day t.

Table 1 reports summary statistics of our data set. Our measure of investor sentiment, S_{it}, has a mean of 0.867 suggesting that positive sentiment about stocks prevails over negative sentiment on any given day. The variable exhibits substantial dispersion around the mean: the standard deviation is 1.101. Median sentiment is also positive, 0.693. The tone of stock-related news items, NS_{it}, is more neutral on average (0.093) and less disperse than investor sentiment (standard deviation = 0.39). Median news sentiment is exactly 0. The average value of $Attention_{i,\ t}$ in our sample is 1.745, i.e., 4.7 posts per stock and day. The stock-day observations in the top 1% of the attention distribution correspond to 446 posts. In contrast, 23% of all observations correspond to stocks that receive no attention on that day. $\alpha_{i,\ t}$ is the abnormal daily return calculated using the three Fama-French factors plus momentum, and was 5.8 bp on average during our sample period, with a standard deviation of about 330 bp. We also report descriptive statistics for our control variables: $Size_{i,\ t}$, the natural logarithm of one plus market capitalization; PB_{it}, the price-to-book ratio; $Turnover_{it}$, the turnover ratio; $TrVol_{it}$, trading volume for stock i on day t, in RMB; $r_{i,\ t-7:t-1}$, the average daily raw return over the week ending on day $t-1$, i.e., from $t-7$ to $t-1$.

3. Stock-level sentiment and stock returns

In this section, we study whether firm-level sentiment predicts future abnormal stock returns.

To test the sentiment hypothesis, we regress stock abnormal returns on day t on our measure of stock-level sentiment on days from $t-1$ to $t-5$. To account for factors that may correlate with both sentiment and returns, we control for stock size, PB ratio, trading volume, turnover ratio, and stock returns over the previous week. That is, we estimate the following regression equation:

$$\alpha_{i,t} = \beta_0 + \sum_{p=1}^{5} \beta_{1,p} S_{i,t-p} + \text{Controls}_{i,t-1} + \varepsilon_{i,t} \tag{3}$$

where $\alpha_{i,\ t}$ is the abnormal return for stock i on day t, and $S_{i,t-p}$ denotes the investor sentiment for stock i on day $t-p$.

Table 2 reports estimation results for our baseline specification. The estimated coefficient on $S_{i,\ t-1}$ reported in column 1 is positive and significant, which confirms that positive sentiment predicts high abnormal returns on the following day. The association is also economically significant: A one standard deviation increase in sentiment is followed by an 8.14 bp (=1.101 × 7.398) increase in the stock's abnormal return (20% in annualized terms). In contrast, the coefficients on two- to five-day lagged investor sentiment are all negative, which suggests that the effect of sentiment reverts in the days following a high-sentiment day, although the coefficient is only significant at the fourth lag.

While we control for observable stock characteristics in our baseline specification, it could be that some stocks tend to generate more positive social media posts and at the same time, exhibit higher abnormal returns for reasons other than stock sentiment (e.g., exposure to omitted risk factors). To account for time-invariant unobservable stock characteristics, in column 2, we report estimation results when we add stock fixed effects to the regression Eq. (2). The estimated coefficients on the variables of interest are almost unchanged. Therefore, the results of column 1 are not driven by stock time-invariant characteristics that could be correlated with both sentiment and abnormal returns.

Note that the finding that positive (negative) stock returns follows days of high (low) sentiment is also consistent with market-wide sentiment driving stock returns. To discard this possibility, in column 3, we allow for time fixed effects. Although the estimated coefficient on one-day lagged sentiment becomes slightly smaller, it is still positive, significant, and economically important. More specifically, a one standard deviation increase in sentiment is followed by a 5.8 bp (=1.101 × 5.275) increase in the stock's abnormal return on the following day. Estimated coefficients on lagged sentiment become larger in absolute value and significant for all lags considered. We therefore conclude that the association between firm-level sentiment and stock returns that we document in this paper, is distinct from the role of market-wide sentiment that has been reported in the literature on investor sentiment.

As mentioned in the introduction, an important concern regarding our results is the possibility that our measure of individual stock level sentiment simply captures changes in fundamentals about stocks. More specifically, if news about a particular firm reflects in higher sentiment, as measured through the tone of Weibo posts, and investors overreact to news, then we would expect prices to first rise with positive sentiment and then fall, undoing part of the initial gains (De Bondt & Thaler, 1987). To address this possibility, we include in the regression a measure of stock news sentiment, which is defined analogously to investor sentiment using the tone of stock-related news items, for different lags. That is, we estimate the following equation regression:

$$\alpha_{i,t} = \delta_t + \gamma_i + \sum_{p=1}^{5} \beta_{1,p} S_{i,t-p} + \sum_{p=1}^{5} \beta_{2,p} NS_{i,t-p} + \text{Controls}_{i,t-1} + \varepsilon_{i,t} \tag{4}$$

where δ_t and γ_i denote time and stock fixed effects, respectively, and $NS_{i,\ t-p}$ denotes news sentiment for stock i on day $t-p$. Results are displayed in column 4. The coefficient on news sentiment is large, positive, and significant. A one standard deviation increase in the sentiment of news relative to a company is followed by an increase in the stock's abnormal return of 6.9 bp (=0.352 × 19.661). There is, however, no clear evidence of price reversals, suggesting that news becomes fully incorporated into prices permanently. Although the coefficient on one-day lagged investor sentiment becomes marginally smaller, it remains positive and both statistically and economically significant. Moreover, the estimated coefficients on investor sentiment at further lags are very similar to those we find in column 3.

[10] According to the company, SINA News aggregates feeds from news providers, bringing together content from media companies, such as CCTV, Beijing TV Station ("BTV"), China News, Agence France-Presse ("AFP"), Associated Press, Reuters, Getty Images, Nanfang Daily Group, Beijing News, Xinhua Net and Xinhua News Agency. Particularly related to the stock market, Sina News covers all main financial media outlets, including China Securities Journal, Shanghai Securities News, Securities Times and Securities Daily. Given the comprehensiveness of Sina News coverage, we are confident that sentiment inferred from news articles in Sina News is representative of news sentiment across all media outlets.

Table 1
Summary statistics.

	1%	10%	Median	90%	99%	Mean	Std. Dev.	Obs.
Sina Weibo data								
$S_{i,\,t}$	−1.099	0.000	0.693	2.197	4.190	0.867	1.101	1,835,948
$NS_{i,\,t}$	−0.693	0.000	0.000	0.693	1.609	0.093	0.390	1,835,948
$Attention_{i,\,t}$	0.000	0.000	1.609	3.638	6.103	1.745	1.470	1,835,948
Stock Characteristics (Resset data)								
$\alpha_{i,t}$ (in bp)	−634.275	−259.458	−15.775	292.673	891.314	5.804	328.947	1,094,446
$Size_{i,\,t}$	20.750	21.223	22.106	23.544	25.330	22.276	0.958	1,134,116
$PB_{i,\,t}$	0.730	1.260	2.550	6.420	27.480	5.374	61.577	1,193,074
$Turnover_{i,\,t}$	0.090	0.313	1.051	3.429	9.151	1.605	1.814	1,134,116
$TrVol_{i,\,t}$ (Mill. RMB)	0.386	1.156	4.554	21.400	99.100	10.600	30.200	1,134,116
$r_{i,\,t-7:t-1}$	−0.030	−0.013	0.001	0.016	0.048	0.002	0.033	1,704,351

This table reports the summary statistics of the variables employed in the analysis. The sample includes 2526 stocks in the full 2013–14 period. $S_{i,\,t}$ is the sentiment measure computed from stock-related Weibo posts, defined in Eq (1). $NS_{i,\,t}$ is the news sentiment measure extracted from stock-related Weibo posts. $Attention_{i,\,t}$ is the natural logarithm of one plus the number of Weibo posts for stock i on day t. $\alpha_{i,\,t}$ (in bp) is the abnormal return calculated by the four-factor model for stock i on day t. $Size_{i,\,t}$ is the natural logarithm of one plus market capitalization in RMB for stock i on day t. $PB_{i,\,t}$ is the price-to-book ratio for stock i on day t. $Turnover_{i,\,t}$ is the turnover ratio for stock i on day t. $TrVol_{i,\,t}$ is the trading volume for stock i on day t in RMB. $r_{i,\,t-7:t-1}$ is the average daily raw return (in decimal units) during the week ending on day $t-1$ (from $t-7$ to $t-1$) for stock i.

Table 2
Firm-level investor sentiment and stock returns.

	(1)	(2)	(3)	(4)	(5)
$S_{i,\,t-1}$	7.398 (9.23)[c]	8.194 (10.64)[c]	5.275 (5.50)[c]	4.809 (5.67)[c]	3.397 (3.36)[c]
$S_{i,\,t-2}$	−0.722 (−0.70)	−0.526 (−0.51)	−2.531 (−3.51)[c]	−2.366 (−3.63)[c]	−2.570 (−3.86)[c]
$S_{i,\,t-3}$	−1.853 (−1.64)	−1.908 (−1.75)[a]	−2.187 (−2.29)[b]	−1.918 (−2.18)[b]	−2.018 (−2.27)[b]
$S_{i,\,t-4}$	−3.207 (−3.02)[c]	−3.309 (−3.16)[c]	−3.450 (−4.69)[c]	−3.273 (−4.89)[c]	−3.359 (−4.97)[c]
$S_{i,\,t-5}$	−0.766 (−0.60)	−0.621 (−0.51)	−3.543 (−3.03)[c]	−3.407 (−3.10)[c]	−3.520 (−3.17)[c]
$NS_{i,\,t-1}$				19.662 (13.94)[c]	19.244 (14.05)[c]
$NS_{i,\,t-2}$				0.009 (0.01)	−0.171 (−0.12)
$NS_{i,\,t-3}$				0.461 (0.41)	0.475 (0.42)
$NS_{i,\,t-4}$				0.066 (0.06)	0.059 (0.05)
$NS_{i,\,t-5}$				2.741 (1.96)[b]	2.756 (1.97)[b]
$Attention_{i,\,t-1}$					3.946 (3.52)[c]
$Size_{i,\,t-1}$	−9.770 (−6.69)[c]	−74.023 (−8.48)[c]	−7.716 (−4.71)[c]	−95.499 (−10.46)[c]	−97.507 (−10.68)[c]
$PB_{i,\,t-1}$	−0.004 (−0.53)	0.013 (1.76)[a]	−0.002 (−0.33)	0.012 (1.60)	0.011 (1.52)
$TrVol_{i,\,t-1}$	0.000 (1.15)	0.000 (2.43)[b]	0.000 (−0.32)	0.000 (−0.78)	0.000 (−0.97)
$Turnover_{i,\,t-1}$	−8.804 (−7.87)[c]	−8.607 (−7.02)[c]	−9.050 (−7.99)[c]	−9.982 (−9.06)[c]	−10.696 (−9.76)[c]
$r_{i,\,t-7:t-1}$	23.837 (0.14)	114.734 (0.68)[c]	483.938 (3.20)[c]	588.703 (3.88)[c]	572.971 (3.76)[c]
Stock FE	No	Yes	No	Yes	Yes
Day FE	No	No	Yes	Yes	Yes
Obs.	849,591	849,591	849,591	849,591	849,591
Adj. R^2	0.003	0.046	0.016	0.060	0.060

This table reports the results of regressing abnormal returns on lagged investor sentiment. Abnormal returns are in bp and are calculated using the four-factor model. $S_{i,\,t-p}$ is the p-day lagged investor sentiment, as defined in Eq. (1). In columns 4 and 5, we include as a regressor the lagged values of stock-related news sentiment, $NS_{i,\,t-p}$, defined analogously to investor sentiment, for news items. In column 5, we include $Attention_{i,\,t-1}$ which is the natural logarithm of one plus the total number of posts on stock i on day t. Control variables are defined in Table 1. t-stats are in parentheses. Standard errors are clustered at both the stock and day levels.

[a] Significant at 10%.
[b] Significant at 5%.
[c] Significant at 1%.

An alternative interpretation of our results is that our measure of sentiment is correlated with investor attention. The literature on attention predicts that high investor attention is followed by stock price increases, as those stocks receiving more attention will tend to be purchased by retail investors in net terms (Barber & Odean, 2008; Da et al., 2011).

To address this concern, we reestimate Eq. (3) including the lagged value of our measure of attention, as defined in Eq. (4). Column 5 of Table 2 reports the results. Consistent with the findings of Barber and Odean (2008) and Da et al. (2011), higher attention given to a stock is followed by significantly higher abnormal returns.[11] More specifically, a one standard deviation increase in attention is followed by an increase in the stock's abnormal return of 5.8 bp (=1.470 × 3.946), an economically significant association. However, the coefficient on one-day lagged investor sentiment remains positive and significant, although smaller. According to this specification, a one standard deviation increase in sentiment is followed by an abnormal return 3.8 bp (=1.101 × 3.494) higher than average. Coefficients on further lags of sentiment remain negative and significant. These results suggest that attention and sentiment play important but independent roles in the determination of stock prices at the firm level.

One potential concern about our results is the possibility that an increase in systematic risk, not captured by our controls or time-fixed effects, results in both price declines and negative investor sentiment. While we adjust stock returns for risk, our betas are estimated using returns from the previous quarter, and may thus not reflect the effect of a recent shock. To account for this possibility, we compute the standard deviation of daily returns in the previous 2, 3, or 4 weeks, and include it as a regressor. Our estimation results (unreported) suggest that stock return volatility over the previous weeks is not significantly associated

[11] Barber and Odean (2008) use news, unusual trading volume, and extreme returns, as proxies for attention. Da et al. (2011) use Google searches.

Table 3
Regression of return volatility on sentiment.

	(1)	(2)	(3)	(4)	(5)	(6)
	14 days		21 days		30 days	
$S_{i,\ t-7:t-1}$	0.0009 (1.79)[a]		0.0005 (0.92)		0.0003 (0.62)	
$\|S_{i,\ t-7:t-1}\|$		0.0004 (0.69)		−0.0001 (−0.18)		−0.0003 (−0.62)
$NS_{i,\ t-7:t-1}$	−0.0023 (−2.28)[b]	−0.0020 (−2.04)[b]	−0.0012 (−1.33)	−0.0010 (−1.13)	−0.0014 (−1.58)	−0.0012 (−1.37)
$Attention_{i,\ t-7:t-1}$	0.0030 (5.76)[c]	0.0032 (5.75)[c]	0.0031 (5.55)[c]	0.0033 (5.61)[c]	0.0032 (5.71)[c]	0.0034 (5.83)[c]
$Vol_{i,\ t-p:t-1}$	0.1093 (8.07)[c]	0.1093 (8.07)[c]	0.0951 (3.81)[c]	0.0951 (3.81)[c]	0.0841 (2.91)[c]	0.0840 (2.91)[c]
$Size_{i,\ t-7:t-1}$	0.0264 (10.32)[c]	0.0264 (10.33)[c]	0.0229 (7.88)[c]	0.0229 (7.88)[c]	0.0195 (6.26)[c]	0.0195 (6.26)[c]
$PB_{i,\ t-7:t-1}$	0.0000 (−1.26)	0.0000 (−1.25)	0.0000 (−1.04)	0.0000 (−1.03)	0.0000 (−0.82)	0.0000 (−0.80)
$TrVol_{i,\ t-7:t-1}$	0.0000 (5.65)[c]	0.0000 (5.64)[c]	0.0000 (5.68)[c]	0.0000 (5.67)[c]	0.0000 (5.75)[c]	0.0000 (5.75)[c]
$Turnover_{i,\ t-7:t-1}$	0.0053 (11.56)[c]	0.0053 (11.54)[c]	0.0048 (8.59)[c]	0.0048 (8.58)[c]	0.0045 (7.67)[c]	0.0045 (7.67)[c]
$r_{i,\ t-7:t-1}$	0.5577 (15.08)[c]	0.5624 (15.22)[c]	0.5227 (15.59)[c]	0.5271 (15.73)[c]	0.4874 (13.78)[c]	0.4923 (13.96)[c]
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	234,311	234,311	234,611	234,611	234,832	234,832
Adj. R^2	0.3726	0.3726	0.3992	0.3991	0.4147	0.4147

This table reports the results of regressing the standard deviation of daily returns over two, three and four weeks on lagged investor sentiment. The dependent variable, $Vol_{i,\ t:t+p-1}$, is defined as the annualized standard deviation of daily raw returns from day t to day $t+p-1$ (in percentage), where p is indicated in the column heading. $S_{i,\ t-7:t-1}$ denotes the average sentiment measure computed from stock-related Weibo posts during the previous week (from day t-7 to day t-1). $|S_{i,\ t-7:t-1}|$ is the absolute value of $S_{i,\ t-7:t-1}$. $NS_{i,\ t-7:t-1}$ is the average sentiment measure computed from stock-related news articles during the previous week. $Vol_{i,\ t-p:t-1}$ is the the standard deviation of daily raw return during the past p days. Attention$_{i,\ t-7:t-1}$ is the average of the natural logarithm of one plus the number of Weibo posts for stock i in the previous week. $Size_{i,\ t-7:t-1}$ is the average of the natural logarithm of one plus market capitalization in RMB for stock i in the previous week. $PB_{i,\ t-7:t-1}$ is the average of the price-to-book ratio for stock i in the previous week. $TrVol_{i,\ t-7:t-1}$ is the average of the trading volume for stock i in RMB in the previous week. $Turnover_{i,\ t-7:t-1}$ is the average of the turnover ratio for stock i in the previous week. $r_{i,\ t-7:t-1}$ is the average daily raw return (in decimal units) during the week ending on day t (from $t-7$ to $t-1$) for stock i. t-stats are in parentheses. Standard errors are clustered at both the stock and day levels.

[a] Significant at 10%.
[b] Significant at 5%.
[c] Significant at 1%.

with subsequent abnormal returns. Moreover, controlling for volatility does not alter our conclusions regarding the association between sentiment and returns.

A related question is whether sentiment can predict volatility. For instance, if social media help reduce information asymmetries, we would expect volatility to decline as investors communicate through social media. On the other hand, if social media propagate investor sentiment information, we would expect volatility to increase. Antweiler and Frank (2004) find that both the number of messages on an internet board and the bullishness of the messages are positively associated with next-day's volatility, which they estimate using intra-daily data. In contrast, Leung and Ton (2015) show in a different sample that the number of messages is negatively associated with next-day volatility, while absolute sentiment is followed by higher volatility in the case of large-capitalization stocks.

In Table 3 we investigate whether sentiment and other variables constructed from our dataset can predict volatility at the weekly frequency. In particular, we regress return volatility over the next 2, 3, and 4 weeks on sentiment, news sentiment, attention, lagged volatility and stock characteristics, all of them measures over the previous week. The results indicate that lagged sentiment is positively, although weakly, associated with volatility over the next two weeks. Attention is also positively and strongly related to subsequent volatility, over the next two, three, and four weeks. Good news, on the other hand, is followed by lower volatility over the next two weeks. Finally, we do not find any significant association between absolute sentiment and subsequent volatility.

Taken together, the results of this section are consistent with a significant role of sentiment on stock prices at the individual-firm level. Such stock-level investor sentiment is distinct from market-wide sentiment or changes in investor attention, and does not simply reflect news.

4. Further evidence

In this section, we consider and test two different implications of the sentiment hypothesis. First of all, it has been argued in the sentiment literature that the magnitude of the effect of sentiment on abnormal returns is stronger for positive sentiment than for negative sentiment (Barber & Odean, 2008). This asymmetry arises because investors can purchase any stock whereas sales are restricted to the stocks they own, without recurring to short sales .

To test this hypothesis, we first disaggregate our investor sentiment into positive investor sentiment and negative investor sentiment:

$$S_{i,t}^{P} = ln(1 + p_{i,t}) \tag{5}$$

and

$$S_{i,t}^{N} = ln(1 + n_{i,t}) \tag{6}$$

where $S_{i,\ t}{}^{P}$ ($S_{i,\ t}{}^{N}$) is the positive (negative) investor sentiment for stock i on day t; $p_{i,\ t}$ and $n_{i,\ t}$ denote the number of Weibo posts with a positive and negative tone for stock i on day t, respectively.

We then regress abnormal returns on lagged positive and negative investor sentiment, while controlling for news sentiment and stock characteristics:

$$\alpha_{i,t} = \delta_t + \gamma_i + \sum_{p=1}^{5} \beta_{1,p} S_{i,t-p}^{P} + \sum_{p=1}^{5} \beta_{2,p} S_{i,t-p}^{N} + \sum_{p=1}^{5} \beta_{3,p} NS_{i,t-p} + \text{Controls}_{i,t-1} + \varepsilon_{i,t} \tag{7}$$

As argued above, we expect the absolute value of $\beta_{1,\ p}$ to be higher than that of $\beta_{2,\ p}$. Table 4 reports the results for different specifications corresponding to the inclusion or exclusion of different fixed effects. In all cases, the coefficients on positive sentiment in the previous day are positive and significant, whereas they become negative and significant for other lags. Therefore, results for positive sentiment are fully consistent with the sentiment hypothesis, regardless of the specification. In contrast, the coefficient on one-day lagged negative sentiment is not significant in any specification, and is in fact, positive. In sum, the results of Table 4 suggest that the link between sentiment and stock returns is fully driven by positive sentiment attracting net purchases from retail investors.

Another implication of the sentiment hypothesis is that sentiment-driven price changes should be followed by price reversals because

Table 4
Asymmetric effects.

	(1)	(2)	(3)	(4)
$S_{i,\ t-1}{}^{P}$	9.870 (9.74)[c]	10.349 (10.18)[c]	7.035 (6.14)[c]	7.749 (7.85)[c]
$S_{i,\ t-2}{}^{P}$	−1.992 (−1.44)	−1.750 (−1.26)	−3.991 (−4.32)[c]	−3.684 (−4.49)[c]
$S_{i,\ t-3}{}^{P}$	−2.553 (−2.00)[b]	−2.489 (−1.94)[a]	−2.513 (−2.46)[b]	−2.369 (−2.48)[c]
$S_{i,\ t-4}{}^{P}$	−3.896 (−3.02)[c]	−3.849 (−2.98)[b]	−3.759 (−4.54)[c]	−3.535 (−4.65)[c]
$S_{i,\ t-5}{}^{P}$	−1.541 (−1.09)	−1.265 (−0.92)	−4.210 (−3.55)[c]	−3.932 (−3.69)[c]
$S_{i,\ t-1}{}^{N}$	0.788 (0.51)	−1.055 (−0.72)	0.110 (0.09)	0.065 (0.06)
$S_{i,\ t-2}{}^{N}$	1.042 (0.94)	−0.021 (−0.02)	1.007 (1.12)	0.720 (0.83)
$S_{i,\ t-3}{}^{N}$	0.943 (0.60)	−0.122 (−0.08)	1.249 (0.88)	0.690 (0.53)
$S_{i,\ t-4}{}^{N}$	2.850 (2.14)[b]	2.035 (1.53)	2.727 (2.14)[b]	2.542 (2.06)[b]
$S_{i,\ t-5}{}^{N}$	3.236 (1.53)	1.966 (0.94)	2.358 (1.27)	2.187 (1.22)
$NS_{i,\ t-1}$	17.511 (14.69)[c]	18.496 (12.99)[c]	18.194 (15.96)[c]	19.165 (13.80)[c]
$NS_{i,\ t-2}$	−1.672 (−1.45)	−0.802 (−0.58)	−0.994 (−0.82)	−0.073 (−0.05)
$NS_{i,\ t-3}$	−1.608 (−1.44)	−0.128 (−0.11)	−0.547 (−0.52)	0.686 (0.61)
$NS_{i,\ t-4}$	−1.888 (0.39)	−0.394 (−0.35)	−1.103 (−0.98)	0.122 (0.11)
$NS_{i,\ t-5}$	1.512 (0.31)	2.137 (1.56)	1.512 (1.22)	2.857 (2.07)[b]
Controls	Yes	Yes	Yes	Yes
Stock FE	No	Yes	No	Yes
Day FE	No	No	Yes	Yes
Obs.	849,591	849,591	849,591	849,591
Adj. R^2	0.004	0.047	0.017	0.060

This table reports the results of regressing abnormal returns on lagged investor sentiment and news sentiment. Abnormal returns are in bp and are calculated using the four-factor model. $S_{i,\ t-p}{}^{P}$ is the p-day-lagged positive investor sentiment. $S_{i,\ t-p}{}^{N}$ is p-day-lagged negative investor sentiment. $NS_{i,\ t-p}$ is the p-day-lagged positive news sentiment. Control variables include lagged stock size, PB ratio, turnover ratio, trade volume, and past return, defined in Table 1. t-stats are in parentheses. Standard errors are clustered at both the stock and day levels.

[a] Significant at 10%.
[b] Significant at 5%.
[c] Significant at 1%.

sentiment captures beliefs that are not justified by fundamentals. This is likely to be the case when we consider the opinions of less sophisticated investors, not of professional investors. For the latter set of investors, we would expect investor beliefs to reflect fundamental information, so if such beliefs impact prices, the effect should be permanent.

Our data provides a unique opportunity to test this hypothesis. More specifically, social media users can voluntarily reveal their identities (e.g., professions) to Weibo, who subsequently marks those users as verified users, or V-users. Typically, they are professionals in finance (e.g., financial analysts, asset managers, and mass media journalists). In our sample, around 13% of Weibo posts are posted by V-users. We construct two separate measures of stock-level sentiment: one using the posts of verified users and one using those of non-verified users. We then regress stock abnormal returns on both measures of sentiment and their lags. That is,

$$\alpha_{i,t} = \delta_t + \gamma_i + \sum_{p=1}^{5} \beta_{1,p} S_{i,t-p}^{V} + \sum_{p=1}^{5} \beta_{2,p} S_{i,t-p}^{NV} + \sum_{p=1}^{5} \beta_{3,p} NS_{i,t-p} + \text{Controls}_{i,t-1} + \varepsilon_{i,t} \tag{8}$$

where $S_{i,\ t-p}{}^{V}$ and $S_{i,\ t-p}{}^{NV}$ denote investor sentiment for stock i on day t-p computed using Weibo posts posted by verified users and non-verified users, respectively.

Table 5 displays the estimation results. In column 1, we report the results without fixed effects. The coefficients on one-day lagged investor sentiment for both verified and non-verified users are positive and statistically significant. The coefficient for verified users (10.9713, $t = 7.05$) is three times larger than that for unverified users (3.0534, $t = 3.98$). More importantly, we do not find evidence of price reversal for verified-user sentiment: Two of the coefficients on lagged sentiment are positive and none of the coefficients are significant. This is in contrast with the coefficients for lagged non-verified-user sentiment. Including stock fixed effects (column 2) or time fixed effects (column 3) or both fixed effects (column 4) does not alter our main conclusions.[12]

In sum, by supporting additional implications of the sentiment hypothesis, the results of this section provide further credibility to the notion that stock-level sentiment matters for stock returns and can be measured from social media data. From a practical point of view, the results also suggest that investors intending to exploit sentiment to predict stock returns should distinguish between different types of social media activity.

5. An instrumental variable approach

While our previous tests alleviate the concern that our results are driven by fundamentals rather than sentiment, they do not allow us to rule out completely the possibility that social media activity picks up on time-varying fundamental information, not included in firm-specific news, that is likely to impact stock returns. Ideally, we would need to observe variation in sentiment that is unrelated to fundamentals.

In this section, we use an instrumental variable approach to address this problem. More specifically, as of November 2014, the regulator requires that all companies with a delisting risk warn their investors that their stock is under risk of delisting. The Exchange will issue a delisting risk warning on the stocks of a listed company upon the occurrence of one or more circumstances from a list, which includes: negative profits in the most recent two consecutive financial years; negative net assets in the latest financial year; audited revenues in the latest financial year below RMB 10 million; failure to comply with disclosure obligations; and fraud and major violation of laws, among others.[13] In the Appendix, we provide an example of this type of announcements.

Such announcements are issued automatically and are known in advance by investors, so they do not contain any new information.

[12] The only change is that the coefficients on verified-user sentiment lagged five days become negative and significant in columns (3) and (4).

[13] For more details on the criteria set by the regulator, please refer to section 13.2 in the “Rules Governing the Listing of Stocks on Shanghai Stock Exchange” and “Rules Governing the Listing of Stocks on Shenzhen Stock Exchange.” The documents can be downloaded from http://english.sse.com.cn/start/rules/sse/public/c/4938268.pdf and http://www.szse.cn/English/rules/siteRule/P020190806407720871488.pdf.

Table 5
Sentiment of professional vs. non-professional users.

	(1)	(2)	(3)	(4)
$S_{i,\ t-1}{}^{V}$	10.971 (7.05)[c]	11.939 (7.35)[c]	8.116 (3.90)[c]	10.097 (6.74)[c]
$S_{i,\ t-2}{}^{V}$	0.788 (0.45)	1.485 (0.85)	−2.622 (−1.54)	−1.163 (−0.90)
$S_{i,\ t-3}{}^{V}$	−1.582 (−0.97)	−1.037 (−0.60)	−1.666 (−1.16)	−0.926 (−0.68)
$S_{i,\ t-4}{}^{V}$	−1.542 (−0.80)	−1.100 (−0.54)	−1.896 (−1.36)	−0.866 (−0.67)
$S_{i,\ t-5}{}^{V}$	1.062 (0.59)	1.879 (0.98)	−4.424 (−2.70)[c]	−3.310 (−2.20)[b]
$S_{i,\ t-1}{}^{NV}$	3.053 (3.98)[c]	3.064 (3.74)[c]	2.688 (4.27)[c]	2.401 (3.51)[c]
$S_{i,\ t-2}{}^{NV}$	−2.018 (−2.49)[b]	−2.300 (−3.00)[c]	−2.067 (−3.07)[c]	−2.271 (−3.57)[c]
$S_{i,\ t-3}{}^{NV}$	−1.462 (−1.50)	−1.806 (−1.91)	−1.637 (−1.86)	−1.632 (−1.87)
$S_{i,\ t-4}{}^{NV}$	−3.049 (−3.71)[c]	−3.470 (−4.30)[c]	−2.990 (−4.38)[c]	−3.132 (−4.57)[c]
$S_{i,\ t-5}{}^{NV}$	−2.041 (−1.77)[a]	−2.285 (−1.97)[a]	−2.451 (−2.25)[b]	−2.547 (−2.26)[b]
$NS_{i,\ t-1}$	17.537 (13.43)[c]	17.815 (12.53)[c]	17.692 (14.13)[c]	18.405 (12.91)[c]
$NS_{i,\ t-2}$	−1.344 (−1.05)	−1.040 (−0.77)	−0.921 (−0.69)	−0.250 (−0.17)
$NS_{i,\ t-3}$	−1.172 (−1.08)	−0.275 (−0.24)	−0.423 (−0.42)	0.555 (0.49)
$NS_{i,\ t-4}$	−1.232 (−1.04)	−0.315 (−0.28)	−0.834 (−0.76)	0.145 (0.13)
$NS_{i,\ t-5}$	1.168 (0.94)	2.326 (1.72)[a]	2.015 (1.66)[a]	3.138 (2.28)[b]
Controls	Yes	Yes	Yes	Yes
Stock FE	No	Yes	No	Yes
Day FE	No	No	Yes	Yes
Obs.	849,591	849,591	849,591	849,591
Adj. R^2	0.004	0.047	0.017	0.060

This table reports the results of regressing abnormal returns on lagged investor sentiment and news sentiment. Abnormal returns are in bp and are calculated using the four-factor model. $S_{i,\ t-p}{}^{V}$ is the p-day-lagged investor sentiment calculated from Weibo posts posted by verified users. $S_{i,\ t-p}{}^{NV}$ is the p-day-lagged investor sentiment calculated from Weibo posts posted by non-verified users. $NS_{i,\ t-p}$ is the p-day-lagged news sentiment. Control variables include lagged stock size, PB ratio, turnover ratio, trade volume, and past return, defined in Table 1. t-stats are in parentheses. Standard errors are clustered at both the stock and day levels.

[a] Significant at 10%.
[b] Significant at 5%.
[c] Significant at 1%.

Therefore, if the delisting risk announcement has an impact on stock returns, it is only through investor sentiment and not fundamentals, which makes it a particularly suitable instrument for our measure of sentiment.

We obtain the delisting risk warning announcement from cninfo.com.cn, which is a designated information disclosure media by the regulator. The webpage is well-known by Chinese investors and it stores all public announcements. The media provide categorized announcements. We manually choose the announcements under the category "Special Treat and Delisting." We require that the titles of announcements include both "delisting" and "reminder." Finally, we identify 227 delisting risk warnings from November 2014 to June 2015 and extend our data set on stock returns and other characteristics to cover this period.[14] We then perform an instrumental-variable regression of abnormal returns on lagged investor sentiment, $S_{i,\ t-1}$, and average investor sentiment in the previous four days, $S_{i,\ t-5:t-2}$. More specifically, both sentiment measures are instrumented with two dummy variables: an indicator variable that equals one if the stock releases a delisting risk warning announcement on day $t-1$ and an indicator for an announcement on any day from $t-5$ to $t-2$. By aggregating lagged sentiment beyond 1 day, we avoid including many instruments, which is known to bias two-stage-least-squares estimates.

For the sake of brevity, we only report the second-stage regression results in Table 6 for different specifications. Results from the first-stage regressions are available upon request and confirm the relevance of the instruments: investor sentiment decreases when a delisting risk warning announcement is issued or has been recently issued. As for the second-stage regression, the coefficients on $S_{i,\ t-1}$ are positive and significant and those on $S_{i,\ t-5:t-2}$ are negative and significant across all specifications.

In the table, we also report the Kleibergen-Paap rk LM statistic and Cragg-Donald Wald F statistic for the underidentification hypothesis and the weak instrument test. We reject the null hypotheses that our IVs are irrelevant or weak.

One possible concern is that our instrumental variable, delisting risk warning announcements, coincides with other negative announcements that may potentially affect both prices and sentiment. To alleviate this concern, we reestimate the regression equation with both time and stock effects, including only those events in which there is no other announcement in the five trading days prior to the event. Column 5 reports the results, which are very similar to those of column 4.

Another possible concern about these results is the relatively large magnitudes of our coefficients. However, it must be noted that our treatment group is not randomly selected from the universe of stocks. In particular, stocks that announce delisting warning are typically glamour stocks with an average PB ratio of 93.16, which is much higher than the rest of the sample (9.91). It seems plausible that those stocks are more prone to investor sentiment. Therefore, while our IV regression results allow us to interpret our results in causal terms, we should not consider the size of such an effect as being representative of the entire universe of stocks.

To alleviate the concern that our treatment and control groups differ along important dimensions, we limit our control group to stocks with a similar likelihood of issuing a delisting risk warning announcement, based on observable characteristics. More specifically, we first estimate the propensity score of each stock using logistic regression, which measures the probability of stock i having a delisting announcement based on its characteristics: lagged stock size, PB ratio, turnover ratio, trade volume, and past average raw return.[15] Then, we limit our control group to the observations with the top 10%, 5% and 1% propensity scores and rerun our instrumental variable regressions. The results are shown in Table 7 and are qualitatively similar to those reported in Table 6. The only notable difference is that the Kleibergen-Paap rk LM statistic is not significant and the Cragg-Donald Wald F statistic is smaller than the Stock-Yogo weak ID test critical values with 10% maximal IV size when the control group is the observations with top 1%

[14] Unfortunately, we have no news data for 2015, so we do not include news sentiment in our regressions.

[15] We use the average raw return during the past six months, which gives a better fit of the model to the data. We also use the average raw return during the past week as in other regressions. The results of the logit regression are available from the authors.

Table 6
Instrumental variable regression, second stage.

	(1)	(2)	(3)	(4)	(5)
$S_{i,\ t-1}$	381.464 (2.79)[c]	347.635 (3.25)[c]	333.944 (4.16)[c]	321.735 (4.52)[c]	328.557 (4.23)[c]
$S_{i,\ t-5:t-2}$	−384.973 (−1.81)[a]	−397.090 (−2.02)[b]	−318.879 (−2.56)[b]	−318.247 (−2.53)[b]	−335.361 (−2.77)[c]
Controls	Yes	Yes	Yes	Yes	Yes
Stock FE	No	Yes	No	Yes	Yes
Day FE	No	No	Yes	Yes	Yes
Obs.	350,837	350,837	350,837	350,837	338,843
Kleibergen-Paap rk LM statistic	2.738[a]	3.494[b]	4.233[b]	4.64[b]	4.247[c]
Cragg-Donald Wald F statistic	11.356	13.642	25.7	28.13	28.877

Note: The Stock-Yogo weak ID test critical values for 10% maximal IV size is 7.03 and that for 15% maximal IV size is 4.58.
This table reports the second-stage results of regressions of abnormal returns on lagged investor sentiment. Abnormal returns are in bp and are calculated using the four-factor model. $S_{i,\ t-1}$ is the 1-day-lagged investor sentiment. $S_{i,\ t-5:t-2}$ denotes investor sentiment averaged over the previous 4 days. Both measures of investor sentiment are instrumented with two dummy variables that equal one if company i issues a delisting risk warning announcement at t-1 and one day from t−5 to t−2, respectively. Control variables include lagged stock size, PB ratio, turnover ratio, trade volume, and past return, and are defined in Table 1. The sample period is from Nov 2014 to June 2015. t-stats are in parentheses. In Column 5, we only delisting risk warnings with no other announcements from day $t-5$ to $t-1$ are included in the analysis. Standard errors are clustered at both the stock and day levels.
[a] Significant at 10%.
[b] Significant at 5%.
[c] Significant at 1%.

Table 7
Instrumental variable regression with propensity score matching[b].

	(1)	(2)	(3)
	Top 10%	Top 5%	Top 1%
$S_{i,\ t-1}$	237.705 (3.30)[c]	185.152 (3.16)[c]	135.183 (3.62)[c]
$S_{i,\ t-5:t-2}$	−164.814 (−1.71)[a]	−88.110 (−1.21)	−42.330 (−1.06)
Controls	Yes	Yes	Yes
Stock Fixed Effect	No	No	No
Time Fixed Effect	Yes	Yes	Yes
Obs	36,229	19,663	6554
Kleibergen-Paap rk LM statistic	3.169[a]	3.009[a]	2.425
Cragg-Donald Wald F statistic	13.48	9.413	5.855

Note: The Stock-Yogo weak ID test critical values for 10% maximal IV size is 7.03 and that for 15% maximal IV size is 4.58.
This table reports the second-stage results of regressions of abnormal returns on lagged investor sentiment using stocks with similar characteristics as control group. The control group is the observations with top 10%, 5% and 1% propensity score. The propensity score is estimated using a logit model for the probability that a firm issues a delisting risk warning with lagged stock size, PB ratio, turnover ratio, trade volume, and past six month average raw return as independent variables. Abnormal returns are in bp and are calculated using the four-factor model. $S_{i,\ t-1}$ is the 1-day-lagged investor sentiment. $S_{i,\ t-5:t-2}$ denotes investor sentiment averaged over the previous 4 days. Both measures of investor sentiment are instrumented with two dummy variables that equal one if company i issues a delisting risk warning announcement at t-1 and ony day from t−5 to t−2, respectively. Control variables include lagged stock size, PB ratio, turnover ratio, trade volume, and past return, and are defined in Table 1. The sample period is from Nov 2014 to June 2015. t-stats are in parentheses. Standard errors are clustered at both the stock and day levels.
[a] Significant at 10%.
[b] Significant at 5%.
[c] Significant at 1%.

propensity score. A possible explanation for the poorer performance of the instrument is the reduced sample size when we keep only 1% of the sample in the regression.

6. Conclusion

Using more than 58 million social media messages on Chinese firms, we construct a measure of investor sentiment at the stock level and examine its ability to predict stock returns. In contrast, the literature has mainly investigated investor sentiment at the market-wide level (Baker & Wurgler, 2006; Da, Engelberg, & Gao, 2015; García, 2013; Hirshleifer & Shumway, 2003; Huang et al., 2015; Marsh & Liu, 2018; Renault, 2017; Stambaugh, Yu, & Yuan, 2012; Xu, Liu, Zhao, & Su, 2017). Studies of firm-level sentiment include Antweiler and Frank (2004); Sprenger et al. (2014), who investigate the US market, and Leung and Ton (2015) who investigate the Australian market.

We find that days of high (low) investor sentiment are followed by statistically and significantly high (low) abnormal returns and price reversal in the subsequent days. These results are robust to the presence of time fixed effects, which enables us to disentangle the effect of stock-level sentiment from that of aggregate sentiment.

We also show that our measure of firm-level sentiment of social media does not just reflect news, is different from attention, and predicts higher stock return volatility, consistent with the investor sentiment hypothesis. Interestingly, opinions posted by sophisticated investors appear to convey fundamental information, rather than propagate investor sentiment.

While isolating the effect of sentiment from fundamentals at the aggregate level can be achieved in a number of ways (e.g., using weather or national sports outcomes), the same task is challenging at the firm level. We overcome this difficulty by exploiting mandated announcements of stale news in the Chinese market.

Our results are potentially useful for active portfolio managers seeking to exploit departures of stock prices from fundamentals. Another potential use of our measure is a means of evaluating market efficiency or investor sophistication for specific stocks or groups of stocks, rather than the market as a whole.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Delisting risk warning announcement

In this appendix, we illustrate what a typical delisting risk warning announcement looks like with an example.

Published by Shanghai KuanPin Technologies Corporate Ltd. (600608) on Apr. 22th, 2015.

Stock Ticker: 600608.

Stock Jiancheng: Shanghai Tech.

Announcement Num. 2015-006.

Title: Shanghai KuanPin Technologies Corporate Ltd. The Third reminder on the delisting risk warning implementation.

Content: The net profit attributable to shareholders of listed company is negative in 2013. Shanghai KuanPin Technologies Corporate Ltd. (the company) predicts that the net profit attributable to shareholders of listed company remains negative in 2014. According to the Rules Governing the Listing of Stocks on Shanghai Stock Exchange, the company may be implemented the delisting risk warning. Now we announce the relative risk for the third time:

1. The company has issued the delisting risk reminders on January 30th, 2015, and April 15th, 2015, respectively: The company financial department estimates that the net profit attributable to shareholders of the listed company is negative in the 2014.
2. According to the Rules Governing the Listing of Stocks on Shanghai Stock Exchange, if the audited net profit is still negative, the company stock would be implemented the delisting risk warning after the 2014 annual financial report is disclosed.
3. The details of company performance is going to be released in the 2014 annual report. The appointed annual report releasing date is April 28th, 2015. The Shanghai Securities News and the Shanghai Stock Exchange Website are the designated information disclosure media. Please be aware of the investment risk.

Hereby announce the above.
The Board of Directors
Shanghai KuanPin Technologies Corporate Ltd.
April 22th, 2015

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