Short Sellers in the Realm of Social Media: Arbitrageurs or Manipulators?[Φ]

Guilong Cai, R. David McLean, Tianyu Zhang, Mengxin Zhao

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Abstract

We study the interaction of short sellers and social media and the effect on stock prices. We use 75.1 million investment-related social media posts for 3,683 unique Chinese firms. Prior to high short interest, social media tone is abnormally positive. Once highly shorted, the tone flips and is abnormally negative. No such pattern exists with traditional media. Compared to firms that are just highly shorted, highly shorted firms with pump-and-dump patterns in social media tone have abnormal returns that are 2.7x higher before, and 3x lower after, the initiation of high short interest. Evidence from natural experiments involving China's introduction and subsequent suspension of shorting also suggest social media manipulation. Manipulation is more likely in firms located in provinces with weaker legal environments. Our findings show that in the realm of social media, short sellers may profit more by creating mispricing than by correcting it.

[Φ] Guilong Cai is at Sun Yat-sen University (caiglong@mail2.sysu.edu.cn), David McLean is at Georgetown (dm1448@georgetown.edu), Tianyu Zhang is at CUHK (tyzhang@baf.cuhk.edu.hk), Mengxin Zhao (mengxin.zhao@gmail.com). We are grateful for helpful comments from Zhi Da, Byoung Hwang, Guofu Zhou and seminar participants at CUFE and Renmin University. We are grateful for data support from DataGo Technology Ltd.

In this paper, we study the interaction between short sellers and social media and the impact on stock prices. One hypothesis is that the combination of short sellers and social media leads to more efficient markets. The finance literature typically assumes that short sellers are informed traders that have a stabilizing effect on prices. Diamond and Verecchia (1987) reason that because short selling is costlier than buying, short sellers are more likely to be informed investors. The findings in many empirical studies support this argument. (e.g., Dechow et al. (2001), Duan, Hu, and McLean (2010), Boehmer, Jones, and Zhang (2008), Engelberg, Reed, and Ringgenberg (2012), Chang, Lou, and Ren (2014), and Ljungqvist and Qian (2016)). A number of studies also find that social media plays an informative role with respect to stock prices (e.g., Chen, De, Hu, and Hwang (2014), Bartov, Faurel, and Mohanram (2017), Giannini, Irvine, and Shu (2017), and Tang (2018)). It could therefore be the case that short sellers use social media to share their information, letting other investors know that prices are too high. This in turn could encourage informed trading that brings prices more in line with fundamentals.

Alternatively, short sellers could use social media to manipulate stock prices. Although academics generally find a positive role for short sellers, regulators have expressed concern that short sellers may manipulate prices. A recent and salient example is the U.S. SEC's investigation into whether the 2021 rise and fall of GameStop's stock price was encouraged by social media manipulation.[1] The SEC has previously charged short sellers with spreading false rumors, and in 2008 issued emergency disclosure rules to limit such activities.[2] Other regulatory bodies have expressed similar concerns. In 2011, the European Securities and Markets Authority stated:

[1] See here: https://www.bloomberg.com/news/articles/2021-02-03/sec-hunts-for-fraud-in-social-media-posts-that-drove-up-gamestop.

[2] See here: https://www.sec.gov/news/press/2008/2008-209.htm

"While short-selling can be a valid trading strategy, when used in combination with spreading false market rumors this is clearly abusive."[3] Social media can be a very effective tool to spread rumors. Consistent with this idea, Jia, Redigolo, Shu, and Zhang (2020) provide evidence that Twitter exacerbates speculative merger rumors. Thus, our alternative hypothesis is that short sellers use social media to manipulate prices, and thereby make markets less efficient.

To test these competing hypotheses, we turn to China. China currently has the world's second largest stock market and may have the world's largest economy within a decade.[4] Studying short sellers and social media in China has several advantages relative to other countries. We have access to a proprietary social media dataset that includes 75.1 million posts on Guba, covering 3,683 unique firms, during the period 2009 to 2018. Guba is one of the oldest and most influential social media platforms that focuses on the Chinese capital market.[5] To the best of our knowledge, this is the largest sample of investment-related social media posts used in the finance literature to date.

Chinese studies generally find that short sellers in China are like short sellers in other countries, i.e., sophisticated investors that profit by shorting overvalued stocks (e.g., Chang, Lou, and Ren (2014)). However, shorting was not allowed in China prior to March of 2010, when the Chinese government began a pilot program. We can therefore study how social media and other factors change when a firm enters the program. In addition, since short selling was introduced in China there was a period during which regulators made security lending very costly, which

[3] See here: https://www.investmentnews.com/countries-ban-short-selling-in-short-order-38151
[4] See here: https://www.bloomberg.com/graphics/2016-us-vs-china-economy
[5] Guba data are also used in Hong, Jiang, Wang, and Zhao (2014) and Piotroski, Wong, and Zhang (2017).

effectively halted short selling. This period further serves as a natural experiment for us to study how social media changes when the ability to short sell changes.

We begin our study by examining how social media tone and traditional media tone evolve when a firm is targeted by short sellers. We find that there is a pump-and-dump pattern in social media tone around periods of high short interest. During the 30 days before a firm is highly shorted, its social media tone is abnormally positive. Once the firm is highly shorted, its social media tone turns abnormally negative. We find no such pattern with traditional media tone.

Short selling began in China in 2010 when the government introduced a program to allow shorting in selected firms. The program provides a nice setting for us to study the effects of short selling. Once a firm is in the program it is shortable, however whether a firm will be selected into the program or not is unknown to the public beforehand. We find that there is no change in social or traditional media tone in weeks before the firm enters the program. However, we find that during the first week a firm is in the program, its social media tone turns abnormally negative if it is highly shorted, while there is no change in its traditional media tone.

We compare the number of social media posts and the volatility of social media tone in the months before and after firms enter the program and become shortable. We find that both are higher after a firm is shortable, and that these effects are not observed with traditional media tone. Social media tone volatility can increase with pump-and-dump manipulation because stock prices are first manipulated up with positive social media tone, and then down with negative social media tone.

Short selling was effectively halted in China by regulators during the months of August 2015 through March 2016. During these months, both the number of social media posts and the volatility of tone decreased for firms that were shortable, but not firms that were not shortable. These effects were not observed with traditional media.

We ask what types of stocks are more likely to have the combination of high short interest and pump-and-dump social media tone. Our findings show that it is more common in larger, more liquid stocks with greater institutional holdings. Institutional holdings is necessary for shorting, as it represents the supply of lendable shares. Targeted firms also have higher market-to-book ratios and higher leverage, i.e., more speculative firms. The likelihood that a firm is targeted increases with the number of posts, especially from more active Guba users. Finally, targeted firms are more likely to be domiciled in provinces with weaker legal environments. Firms in such provinces tend to be less transparent and there is less enforcement of self-dealing. Thus, investors may be less confident in the information coming from such firms, giving rumors more strength.

We then study the impact that social media tone and short interest have on stock returns. We find that they interact. Highly shorted firms have abnormally high (low) stock returns before (after) the initiation of high short interest. These effects are greater if the shorted firms also have pump-and-dump patterns in social media tone around the initiation of high short interest. As compared to firms that are just highly shorted, stocks that are both highly shorted and have pump-and-dump patterns in social media tone have abnormal stock returns that are 272% higher before, and 306% lower after, the initiation of high short interest.

We consider the idea that highly shorted stocks with pump-and-dump patterns in social media tone are not manipulated, but instead have impending bad news and short sellers trade ahead of this. If this is the case, then in the subsequent period the low returns should occur primarily in firms with more traditional news stories. Yet we find that opposite: the abnormally low returns of highly shorted stocks with pump-and-dump patterns in social media tone occur more strongly in firms with fewer traditional news stories.

One question is whether our findings are only relevant for the Chinese stock market, or do they extend to other markets as well? As we mention above, earlier Chinese studies find that short sellers are sophisticated investors that buy overvalued stocks, which is what U.S. studies and international studies also find. So it could be that short sellers also manipulate prices with social media in other countries, but it has not been documented yet. The Chinese stock market is more dominated by retail investors, whereas the U.S. market is more dominated by institutional investors, and social media is likely to have more of an influence on retail investors, so from this perspective what we document could be more of a Chinese phenomenon. There is evidence though that retail investors in the U.S. provide liquidity and impact prices. We know this from highly visible anecdotes (e.g., GameStop) as well as academic studies (e.g., Kaniel et al. (2012) Kelly and Tetlock (2013)). As we mention earlier, China is the world's second largest economy and stock market, and given its increasing economic importance understanding Chinese capital markets seems important in its own right.

Our findings contribute to several branches of literature. With respect to short selling, we are the only paper that we know of to provide systematic evidence that short sellers manipulate stock prices. Virtually all papers in this field show that short sellers make prices more efficient, be it in the U.S. (e.g., Dechow et al. (2001), Boehmer, Jones, and Zhang (2008), and Duan, Hu, and McLean (2010)), China (e.g., Chang, Lou, and Ren (2014)), or around the world (Bris, Goetzmann, and Zhu (2007)). Ljungqvist and Qian (2016) even report examples of U.S. short sellers releasing informative, private information via traditional media. Our paper shows that short sellers can also play a destabilizing role when in the presence of social media, which is an increasingly common form of media and communication.

Our paper has ramifications for asset pricing theory, as it shows that social media can influence the way that sophisticated investors (arbitrageurs) impact prices. Most theories in finance assume that arbitrageurs have a stabilizing effect on prices.[6] This is the case in classical finance, where markets are assumed to be efficient, (e.g., Freidman (1953)), as well as in most behavioral finance theories, in which equilibrium prices do not reflect fundamentals, but arbitrageurs' trades still make markets more efficient (e.g., Figlewski (1979), De Long et al. (1990a), Shleifer and Summers (1990) and Barberis and Thaler (2003)). None of these papers include a role for social media, which did not exist when most of them were written. Our findings show that when social media is added to the mix, arbitrageurs may make markets less efficient. One paper in this spirit is De Long et al. (1990b) who find that arbitrageurs further destabilize prices when in the presence of feedback traders.[7] Another is van Bommel (2003), who creates a model in which investors spread rumors, causing other investors to trade and prices to diverge

[6] Like Shleifer and Summers (1990) we think of markets consisting of two types of investors: arbitragers who are the "smart money" or "rational speculators" and everyone else.

[7] Feedback trading can be caused by extrapolative expectations about prices, trend chasing, and even stop-loss orders. De Long et al. (1990b) point out that feedback trading is recognized as far back as Bagehot (1897) and that feedback trading is perhaps the most well-documented type of "noise trading". De Long et al. (1990b) are inspired by Soros (1987), who claims to have traded in this spirit during the 1960s conglomerate bubble and the 1970s REIT bubble.

from fundamentals. The rumormongers then trade on and profit from the mispricing, which is what we seem to find.

Our paper also builds on studies based on U.S. data study the effects of stock message boards. Tumarkin and Whitelaw (2002) and Antweiler and Frank (2004) find that message tone is positively correlated with contemporaneous returns, but does not predict future returns. Similarly, Das and Chen (2007) find that message sentiment reacts to returns, but does not predict returns. Cookson, Engelberg, and Mullins (2020) find that stock message board users tend to follow users that post similar beliefs about the same stocks. None of these papers study relation between short sellers and social media, which is our focus.

1. Data, Sample, and Variables

1.1. Social Media Data

We use posts from Guba of East Money, which is one of the oldest and most influential social media platforms focusing on the capital market in China. We design an automatic crawler to get all the main posts, ignoring the replying posts, for each firm.[8] We require each firm to have at least three social media posts per day to avoid errors in our measurement of daily social media tone. Our social media dataset includes about 75.1 million posts, covering 3,683 unique firms over the period 2009 to 2018.

1.2. Traditional Media Data

[8] We filter the posts, such as news articles, that are automatically posted by the platform by tracing the hyperlink.

The traditional media data is an updated version of that used in Piotroski, Wong, and Zhang (2017). We use articles published in official newspapers and non-official newspapers focusing on financial and economic news. We collect data from Wisenews[9], a database that archives all historical articles published by a variety of newspapers and magazines in Chinese. Our traditional media dataset includes about 2.01 million articles, covering 3,603 unique firms from 2009 to 2018.

1.3. Firm-Sample

We begin our sample with all available firm-day short interest for the period March 31, 2010 to December 31, 2018. This yields 1,248,302 observation. Short-selling was prohibited in China prior to March 31, 2010. We drop 84,778 observations from financial industries and 38,317 observations with missing data that are needed to construct our main variables. Our final sample includes 1,125,207 firm-day observations from 1,013 unique firms.

1.4. Variables

The primary variables in this paper are concerned with the measurement of short selling and the tone of the posts from social media and news articles from traditional media. We describe how we construct these variables along with some other firm-level variables below.

Measuring Media Tone. We utilize machine learning techniques to construct the tones of news articles from traditional media and posts from social media. The resulting data are also used in Wang, Wong and Zhang (2021). A team of research assistants, including undergraduate and

[9] https://www.wisers.com.cn/hk/home/index.html

postgraduate business school students labeled the tone of each sentence of 50,000 articles randomly picked from our sample as negative, positive, and neutral. Using these manually labeled training materials, we train a support vector machine (SVM) model to classify each sentence into positive, neutral, or negative and check the out-of-sample classification accuracy using a subset of manually labeled sentences that the model has not seen. The out-of-sample validation using 10,000 randomly selected sentences shows that the accuracy rate of our model is above 90%.

The tone of the article is measured by the relative weight of positive sentences to negative sentences in the article. In addition, we also consider the importance of sentences from different positions within an article. We weigh the sentences from the first and last paragraphs as 2, the first and last sentences of the first and last paragraphs as 3, and other sentences from the article as 1. The tone of the article's body equals (#of positive sentences−# of negative sentences)/(#of positive sentences+# of negative sentences+1).[10] The overall tone of the article, in the end, is defined as (tone of text body*0.7+tone of title*0.3).

For the posts from Guba, we label the training set at post level rather than at sentence level because the post are normally short. In total we label 50,000 randomly selected posts as the training set and then classify all the posts into positive, negative and neutral using SVM. Given the linguistic feature, we also consider the emoji of social media in our modeling.

Table 1 displays summary statistics for the media variables. The mean values are positive for the traditional media variables and negative for the social media variables. It is well-

[10] We put more weight on the title and certain sentences in the text following Njølstad et al. (2014) and Yang et al. (2014).

documented that traditional media in China has a positive bias, which is present in corporate news (Stockmann (2013) and Piotroski et al. (2017)). Autocratic governments, such as the one in China, tend to influence the media so as to protect their political power. Negative corporate news may harm the economy and the public's perception of the government's competence, thus the positive bias in corporate news. Wang, Wong, and Zhang (2021) document that this positive bias in Chinese corporate news is at least in part offset by negative posts in social media, which may explain why the mean values are negative for the social media variables.

Short Interest. We measure short interest each day as the ratio of the number of shares shorted divided by the number of shares outstanding. We rank all firms for which shorting is possible according to their short interest for each year. If at any trading day during the year that a firm crosses the 90 percentile, we refer to the day as highly shorted for the firm. In unreported tests we get similar findings using the 95th percentile as our cutoff. We have also used continuous short interest in our tests, and get similar findings. Table 1 shows that the mean value of short interest in our sample is 0.011 and the standard deviation is 0.016. For firms that are highly shorted the mean level of short interest is 0.047 and the standard deviation is 0.023.

[Insert Table 1 here]

Other Firm-Level Variables. We also use several firm-level variables in our tests. These data are obtained from the Chinese Securities Market and Accounting Research (CSMAR). To control the firm fundamentals, we include firm size (*SIZE*), leverage (*LEV*), book-to-market ratio (*BM*), return on total assets (*ROA*), and the cumulative abnormal return over the 30 days [t-60 to t-30] prior to our test window (*PRERET*). We also include an indicator variable, *SOE*, to capture the political bias for state-owned enterprises. The construction of these variables is detailed in the appendix. We report the sample distribution by year and by industry in Table 2.

[Insert Table 2 here]

2. Short Selling and Social Media Tone

In this section, we discuss our findings regarding media tone around short selling. We test whether the evolution of social media tone around the initiation of high short interest is consistent with manipulative trading. We also ask whether any patterns in social media tone are mirrored by similar patterns in traditional media tone. A similar pattern between social media and traditional media suggests that social media is reflecting actual news, rather than manipulative trading.

2.1. Short Selling and Social Media Tone

The regressions reported in Table 3 test how social media tone evolves around the initiation of high short interest. The unit of observation is firm-day. The dependent variable is the average daily social media tone measured over various periods. We measure social media tone over the intervals of *t-30* to *t* and *t-5* to t, and then *t+1* to *t+5* and *t+1* to *t+30*. We regress social media tone on a dummy variable equal to 1 if the firm becomes highly shorted on day *t*, and zero otherwise. We control for size, profitability, leverage, book-to-market, lagged stock returns, and whether the firm is a state-owned-enterprise. We also control for traditional media tone, measured over the same horizon as social media tone. The regressions include firm and time fixed effects, and the standard errors are clustered on firm.

[Insert Table 3 here]

In the first regression, the dependent variable is the average social media tone over the period *t-30* to *t*. The coefficient for the day *t* high short interest dummy is 0.008 (*t*-statistic = 3.10). This shows that social media tone is abnormally positive over the 30 days before a firm becomes highly shorted. Regression 2 studies social media tone over days *t-5* to *t* and finds the same effect. With respect to economic significance, the mean of social media tone is -0.214 over the *t-30* to *t* period (see Table 1). The dummy variable in regression 1 thus shows that the social media tone is higher by about 3.7% relative to the mean, while in regression 2 the effect is 4.2% higher relative to *t-5* to *t* period's mean.

Regressions 3 and 4 study social media tone after the firm becomes highly shorted, over 5 -day and 30-day horizons, respectively. We find that the tone flips. In both specifications, the effect of being highly shorted is associated with abnormally negative social media tones. In regression 3, the coefficient is -0.005 (*t*-statistic = -3.89). This shows that the tone is abnormally low by about 2.3% relative to the mean over the 5 days after a firm becomes highly shorted. Regression 4 shows that the effect grows, and is 4.3% lower relative to the mean over the 30-day horizon. Hence, once short sellers target a stock there is a negative and statistically significant change in its social media tone.

The results in Table 3 also show that social media tone is more positive if the firm has high past stock returns and is a glamour stock (low book-to-market ratio), which is sensible. The traditional media tone coefficient is positive and significant in all specifications. This is also sensible, it shows that when the traditional news tone is more positive, social media tone is also more positive. It also shows that the relation between short interest and social media tone cannot be explained by social media tone simply reflecting traditional media tone, as traditional media tone is controlled for.

2.2. Short Selling and Traditional Media Tone

The results thus far show a pump-and-dump pattern in social media tone around high levels of short interest. That is, if a firm has a high level of short interest on day *t*, the tone of the social media concerning the firm was abnormally positive over the days leading up to and including day *t*, and then abnormally negative over the days following day *t*. This pattern is consistent with short sellers attempting to manipulate stock prices via social media. However, the pattern could also reflect social media participants discussing actual news about the firm. Perhaps the firm had good news before it was highly shorted and then bad news afterwards? Although we control for traditional media in our social media tests reported in Table 3, we explore this issue further here.

We re-estimate the regression reported in Table 3, however, we replace social media tone with traditional media tone as the dependent variable. If the same pump-and-dump pattern reported in Table 3 is not observed with traditional media tone, then it is unlikely that the social media tone patterns in Table 3 reflect actual news.

The first two regressions in Table 4 study traditional media tone over periods *t-30* to *t* and *t-5* to *t*. In both specifications, the high short interest coefficient is insignificant. Regressions 3 and 4 study the traditional media tone over the 5-day and 30-day periods after the firm is highly shorted. The high short interest coefficient is positive but insignificant over the 5-day horizon, and then negative and marginally significant over the 30-day horizon. The coefficient over the 30-day horizon is -0.009 (*t*-statistic = -1.67), showing that the traditional media tone is lower 2.8% over the period. This is not surprising, as highly shorted stocks are expected to have some bad news, however the effect is 35% less than that measured in Table 3 with social media tone over the same horizon, and the *t*-statistic is also much smaller (1.67 vs. 5.45 in Table 3). Overall, the pump-and-dump pattern in social media tone observed in Table 3 is not observed in Table 4 with traditional media.

The control variables in Table 4 show that larger and more profitable firms have more positive traditional news tone. Table 3 shows that social media tone is unrelated to both of these variables. As with social media tone, traditional media tone is more positive for growth stocks and stocks with high past returns. Finally, as we saw in Table 3, traditional media tone and social media tone are positively correlated, as the social media tone coefficient is positive and significant in all of the specifications.

[Insert Table 4 here]

3. Natural Experiments from the Short Selling Pilot Program and its Temporary Suspensions

Short selling began in China in March 2010 with a pilot program that allowed shorting of selected firms. Once a firm enters the program shorting is allowed, however which firms will be selected on which dates is not known ahead of time by market participants. In addition, during the months August 2015 through March 2016 regulators increased the cost of short selling significantly, which effectively halted short selling during these periods.[11] Thus, the introduction

[11] On August 4th, 2015, the exchange changes the trading rules for short sell from t+0 to t+1. The new rule was that the short seller cannot repay the borrowed shares on the same day, increasing the cost of short sell significantly. On

of short selling and this temporary stoppage serve as natural experiments with which we can test for the effects that shorting has on social media. Thus far our results suggest that short sellers use social media to manipulate stock prices, and these events allow us to further test this hypothesis.

3.1. The Short Selling Pilot Program and Social Media Tone

We begin by studying how a firm's social media tone changes once it enters the short selling pilot program. Our sample again consists of firm-day observations; however, the observations are limited to the first five days that a firm is in the shorting program. We expect that the abnormally positive social media tone prior to high short interest, documented in Table 3, will not appear for firms that are new entrants to the shorting program. This is because short sellers don't know which firms will enter the program, so they cannot manipulate via social media beforehand. We do though, expect to find the abnormally negative social media tone for highly shorted firms, as was documented in in Table 3.

We report the findings from these tests in Table 5. The first two regressions in Table 5 study social media over the periods *t-30* to *t* and *t-5* to *t*, where day *t* refers to the day that short interest is measured and is limited to the first 5 days that the firm is in the short selling program. The results in Table 5 show that there is no difference in social media tone between firms that become highly shorted and firms that do not become highly shorted during this period. This

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the second day, majority of the brokers suspended their business of lending shares, which was not restored until March 2016.

makes sense, as it is not known ahead of time that a firm will enter the program and that shorting will be allowed.

[Insert Table 5 here]

Columns 3 and 4 report the effects of high short interest on social media tone during the periods *t+1* to *t+5* and *t+1* to *t+30*. The results show that the social media tone becomes abnormally negative for firms that are targeted by short sellers. In the third column, which measures social media tone during the period *t+1* to *t+5*, the high short interest coefficient is -0.036 (*t*-statistic = -2.52). This reflects a 17.56% decline in social media tone relative to the mean value of social media tone reported in Table 1. The high short interest coefficient in the fourth column reflects a 15.24% decline in social media tone during the period *t+1* to *t+30*.

Taken together, the results in Table 5 show that once a stock becomes shortable and targeted by short sellers, its social media tone turns abnormally negative. This finding, taken together with those in Tables 3 and 4, are consistent with the idea that short sellers use social media tone to manipulate stock prices.

3.2. The Short Selling Pilot Program and Traditional Media Tone

Table 6 is like Table 5, only it studies traditional media tone. Our sample again consists of firm-day observations that are limited to the first five days that a firm is in the shorting program. In the first two columns, the high short interest coefficient is positive but insignificant in both the *t-5* to *t* window, and in the *t-30* to *t* window. In columns 3 and 4, the high short interest coefficient is positive and insignificant in the *t+1* to *t+5* window, and negative but insignificant in the *t+1* to *t+30* window. Hence, unlike social media tone, traditional media tone does not become abnormally negative once a firm enters the program and becomes highly shorted.

[Insert Table 6 here]

3.3. The Number of Social Media Posts and Volatility of Social Media Tone

Table 7 further studies the effects of entering the short selling pilot program. We now use monthly data, and study how social media and traditional media change when a firm enters the shorting program. Our tests so far suggest that short sellers may use social media to manipulate stock prices. If this is the case, then we would expect there to be more social media posts for firms in the program, and for the volatility of tone to increase, as the pattern we observe around shorting is abnormally positive tone followed by abnormally negative tone.

We measure the number of social media posts and the standard deviation of tone for each firm-month observation. In China, firms enter the shorting pilot program in different batches (staggered events), and there are still many firms that cannot be shorted. The sample in Table 7 includes all firm-month observations for all listed firms from 2010 January to 2018 December, including firms that never entered the program. We create a dummy variable equal to 1 if the firm-month is shortable and zero otherwise. Once a firm enters the program it tends to stay in, i.e., the dummy variable remains equal to 1. Our regressions include firm and time fixed effects, so technically we are estimating Difference-in-Difference models, i.e., the coefficient is the difference between the pre and post for firms that enter the pilot program, compared to firms that never enter the program.

The first regression in Table 7 shows that the number of social media posts increases once a firm enters the program. The dependent variable is the log of one plus the number of social media posts in month *t*. The coefficient for the shorting dummy is 0.084 (*t*-statistic = 4.16), showing that the number of posts is significantly higher once a firm enters the program. The dependent variable is a log, and exponentially transforming the short selling coefficient shows that the number of posts is 8.76% higher after shorting is allowed compared to before.

The regression reported in column 2 uses the standard deviation of media tone as its dependent variable. We control for the number of social media posts. The short selling dummy in this specification is 0.003 (*t*-statistic = 4.40), showing that volatility of social media tone increases after a firm enters the short selling pilot program.

The regressions reported in columns 3 and 4 report what happens when short selling was temporarily suspended among firms that were shortable. As we explain earlier, between August 2015 and March 2016, most security lenders temporarily stopped lending shares in China, so short selling was effectively halted. For these specifications, we limit our sample to firms that can be shorted, and test whether the number of posts and volatility of social media tone dropped during the suspension months.

In both regressions 3 and 4, the dummy for the short selling suspension is negative and significant, showing that both the number of posts and the volatility of social media tone declined when short selling was temporarily halted. In regression 3, exponentially transforming the no-shorting coefficient shows that the number of social media posts declined by 12.28% during the months in which short selling was halted. The no-shorting coefficient in regression 4 reflects about a 1.25% decrease in the volatility of social media tone during the no-shorting months.

[Insert Table 7 here]

3.4. The Number of Traditional News Articles and Volatility of Traditional Media Tone

Table 8 repeats the same regressions that are reported in Table 7, only we replace social media with traditional media. The first two regressions in Table 8 show that the number of traditional media articles and the standard deviation of the articles' tone did not increase for firms that entered the short selling pilot program. This is in contrast to the results in Table 7, which show that both the number of social media posts and the volatility of social media tone increased significantly for firms that entered the shorting program. Hence, the changes in social media documented in Table 7 are not a reflection of traditional media news stories.

Regression 3 shows that when short selling was suspended, the number of traditional news stories did not change significantly. This is again in contrast to Regression 3 in Table 7, which shows that there was a significant decline in social media posts when shorting was suspended. Regression 4 shows that the volatility of tone in traditional media actually increased when short selling was temporarily halted. This is opposite to the findings in Table 7, which show that the volatility of social media tone declined when shorting was suspended.

[Insert Table 8 here]

4. What Types of Stocks do Short Sellers Target?

In this section of the paper we study the types of stocks that short sellers target via logit regression models. We create a dummy variable equal to 1 if a firm is highly shorted and has pump-and-dump social media tone, i.e., social media tone that is above (below) the sample median before (after) the day short interest is measured. We measure social media tone over 5-day (30-day) periods in column 1 (column 2) of Table 9.

The results reported in Table 9 reveal several interesting findings. Targeted stocks tend to be larger, more liquid, and have greater institutional holdings. The institutional holdings effect makes sense. In order to short a firm its shares have to be borrowed, and the lenders are almost always institutions. In the U.S. one might expect negative coefficients for the size and liquidity variables, however in China trading is dominated by retail investors, so one might expect to see manipulation and mispricing in larger, more liquid firms.

There is more manipulation in growth stocks (low book-to-market) and in stocks with higher leverage. This also make sense, as growth stocks are more likely to be overvalued, and it is easier to spread rumors and influence sentiment in more speculative firms. The past return variable, which reflects past returns over the previous fiscal year is negative and significant, so targeted firms have had some earlier unwinding in the their valuation.

The coefficient for the *Law* variable is negative and significant. The *Law* variable is from Fan and Wang (2001) and reflects the provincial legal environment. Higher values of *Law* reflect a province with stronger legal environment, i.e., more required transparency and more enforcement against fraud and self-dealing. Our results therefore show that there is less manipulation in firms that are located stronger legal environments. Firms in stronger legal environments tend to be more transparent and investors may have more trust in the information being disclosed. Manipulation is easier when there is less transparency and less trust in what firms are disclosing. Our results therefore are consistent with the idea that the stronger legal environment can make stock price manipulation more difficult.

We include two firm-level social media variables, *ACTIVEUSERS* and *NONACTIVE*. An active user is defined as a user with posts on Guba numbering in the top decile over the last 3 months. *ACTIVEUSERS* is the number of posts for firm *i* over the measurement period (5 days or 30 days) from active users, scaled by the total number posts over the prior year. *NONACTIVE* is the firm's total posts over the measurement period minus its posts from active users, all scaled by the number of posts over the prior year. We scale by the number of total posts over the prior year to control for the fact that some firms may systematically have more social media attention. The coefficients for *ACTIVEUSERS* and *NONACTIVE* are both positive and significant. However, the *ACTIVEUSERS* coefficient is larger and its significance is greater. In unreported F-tests, we find that the *ACTIVEUSERS* coefficient is significant larger. Thus, when there is an increase in postings from all users and especially active users, the likelihood of a pump-and-dump pattern in social media tone combined with high short interest is greater.

We further study the effects of active users in Panel B, where we replace *ACTIVEUSERS* and *NONACTIVE* with a single variable that is the ratio of *ACTIVEUSERS* to *NONACTIVE*. The coefficient for this variable is positive and significant in both specifications, confirming that when there is more posting from active users the likelihood of social media manipulation combined with high short interest increases.

[Insert Table 9 here]

5. Short Selling and Social Media Tone: The Effects on Stock Returns and Volume

In this section we study how shorting and media tone impact stock returns. A number of earlier studies show that high levels of short interest portend low stock returns in China and in other countries (e.g., Dechow et al. (2001), Duan, Hu, and McLean (2010), Boehmer, Jones, and Zhang (2008), Engelberg, Reed, and Ringgenberg (2012), and Chang, Lou, and Ren (2014)). This is typically interpreted as showing that short sellers are informed investors. We build on this and look for evidence of short-seller manipulation.

5.1. Short Selling, Social Media Tone, and Stock Returns: General Results

Our results thus far show that social media tone is abnormally positive before stocks are highly shorted and abnormally negative once highly shorted. These effects are not explained by social media reflecting actual news, as traditional media follows no such pattern. If such patterns reflect effective manipulation, then firms that have such pump-and-dump patterns in social media tone should also have contemporaneous pump-and-dump patterns in stock returns.

To test for these effects, we regress the period's stock return on a high short interest dummy, a dummy variable that we refer to as *Manipulate*, the high short interest dummy interacted with *Manipulate*, and controls. The variable *Manipulate* is equal to 1 if the firm has social media tone that is above the sample median before and on the day that short interest is measured, and below the sample median after that day, and zero otherwise. As an example, in Regression 1 of Table 10, we study abnormal stock returns over the period *t-30* to *t*. *Manipulate* is equal to 1 if the average daily social media tone was above the sample median over the period *t-30* to *t*, and then below the sample median over the period *t+1* to *t+30*. The control variables include earnings-to-price and size, as Liu, Stambaugh, and Yuan (2019) find that these variables explain the most anomalies in China.

In Regression 1, the coefficients for the high short interest dummy, *Manipulate*, and the interaction between the two are positive and significant. This shows that highly shorted firms, firms with pump-and-dump patterns in social media, and especially firms that have both of these effects have abnormally high stock returns during the 30 days before becoming highly shorted. The coefficient for the high short interest variable is 0.018, for *Manipulate* it is 0.042, and the *Manipulate*-high short interest interaction coefficient is 0.007. Thus, for a firm that is both highly shorted and has a positive value of *Manipulate*, the overall effect is the sum of the coefficients, which is equal to 0.067. The abnormal return effect of having both social media manipulation and high short interest is 272% greater than just having high short interest. Similar findings are reported Regression 2, which studies the effects over a 5-day window. In this regression, abnormal stock returns are 350% higher for highly shorted firms that also have positive values of *Manipulate* as compared to highly shorted firms that do not.

Regressions 3 and 4 examine the post shorting windows. Regression 3 examines returns over the period *t+1* to *t+5*. In this regression, the coefficients for the high short interest dummy, *Manipulate*, and their interaction are all negative and significant. Thus, highly shorted firms have low stock returns, and the effects are greater for highly shorted firms with pump-and-dump patterns in social media tone. Regression 4 studies stock returns over the 30 days subsequent to being highly shorted. The coefficients suggest that stock returns are 306% lower for firms that are both highly shorted and have pump-and-dump social media tones, as compared to firms that are just highly shorted.

Panel A of Table 10 in its entirety shows that stocks that are targeted by short sellers and have pump-and-dump patterns in social media tone have especially large runups and then declines in stock prices. These results are also shown in Figure 1, which displays the cumulative abnormal return for the 30 days before and 30 days after for the initiation of high short interest. Figure 1 shows that stock returns are significantly higher before and significantly lower after for highly shorted firms that also have positive values of *Manipulate* as compared to firms that are just highly shorted. Overall, the findings here are consistent with the idea that short sellers manipulate stock prices via social media.

[Insert Table 10 here]

[Insert Figure1 here]

5.2. Short Selling, Social Media Tone, and Trading Volume

Panel B of Table 10 replaces stock returns with trading volume. We do so for robustness, as we want to be confident that prices and investors are indeed responding to social media tone. The findings in Panel B suggest that this is the case, as the coefficients for *Manipulate* and the interaction between *Manipulate* and the high short interest dummy are both positive and significant in all four regressions. Thus, if a firm is highly shorted and has pump-and-dump patterns in social media tone, its trading volume is greater as compared to a firm that is just highly shorted. The coefficients show that a firm with both high short interest and a positive value of *Manipulate* has trading volume that is about 26% to 71% higher as compared to a firm that is only highly shorted.

5.3. Short Selling, Social Media Tone, and Stock Returns: The Effects of News Events

In this section of the paper, we conduct further tests of whether highly shorted firms with pump-and-dump patterns in social media tone have low returns due to stock price manipulation. As we explain earlier, most academic studies find that short sellers are informed traders. Christophe, Angel, and Ferri (2004) find that short sellers trade ahead of earnings announcements, anticipating which stocks will have poor earnings news. Boehmer, Jones, Wu, and Zhang (2019) find that event days with earnings news or analyst-related information account for 24% of short seller's abnormal returns, even though these days only account for 12% of trading days. Engelberg, Reed, and Ringgenberg (2012) find that the abnormal returns of highly shorted stocks are twice as large following news days as compared to non-news days. Our results thus far show that highly shorted stocks with pump-and-dump patterns in social media tone have abnormally low stock returns. If this somehow reflects informed trading that is reacting to or anticipating bad news, then such stocks should have their abnormal returns following or concentrated on days with news. If instead, the low stock returns reflect social media manipulation, then we would not expect news days to play an outsized rule in accounting for the abnormal returns.

We report results from these tests in Table 11. We study returns over the 30-day period after a firm becomes highly shorted.[12] In column 1, the sample is limited to days with traditional news stories, while in column 2 the sample is limited to days with no traditional news stories. We therefore test whether short interest predicts returns more strongly if the shorting is on a news day vs. a non-news day, which follows Engelberg, Reed, and Ringgenberg (2012). As in Tables 10,

[12] We get similar results using a 5-day window.

we regress stock returns on the high short interest dummy, the variable *Manipulate*, which is equal to 1 if the firm has social media tone above the sample media in the pre-window and below the sample median in the post-window, and an interaction between the high short interest dummy and *Manipulate*.

In column 1, where the sample is limited to days with news, the interaction coefficient is insignificant. That is, highly shorted stocks with pump-and-dump patterns in social media tone do not have abnormally low stock returns follows days with traditional news. In column 2, however, the interaction is negative and significant, showing that the abnormally low returns earned by highly shorted stocks with pump-and-dump patterns in social media tone arise more strongly following days *without* traditional news. This finding is not consistent with the abnormal returns reflecting short sellers processing public information.

Focusing on the high short interest coefficient, the results in Table 11 show that highly shorted stocks have abnormally low returns following both news days and non-news days. The coefficients suggest slightly larger abnormal returns following non-news days, however the returns on news days are highly significant as well. Engelberg, Reed, and Ringgenberg (2012) find that in the U.S., the abnormal returns of highly shorted stocks are twice as large following news days as compared to non-news days. The results here show that in China there is no such effect. This suggests that short selling may be more informed in the U.S. than in China, although Chinese short selling is still informed.

The regressions reported in columns 3 and 4 tell a similar story. In these tests, we sort firms into two groups based on the number of traditional news stories over the subsequent 30-day period. The *More News* group consists of firms having the number of news days (size-adjusted) above the sample median, while the *Less News* group consists of firms having the number of news days (size-adjusted) below the median.[13] Here again, the interaction coefficient between high short interest and *Manipulate* is insignificant in the more news specification, and negative and significant in the less news specification. That is, highly shorted firms with pump-and-dump patterns in social media tone have more their abnormally low returns when there is less actual news. When there is more actual news, some of the abnormally low returns disappear. This is the opposite of what we would expect if the abnormally low returns reflected the anticipation of bad news by short sellers.

6. Conclusion

Earlier studies find that short sellers play a stabilizing role in stock markets. This is found in studies using U.S., Chinese, and Global data. The common interpretation is that short sellers are informed investors that target overvalued firms and that short sellers' trades therefore encourage market efficiency. This narrative is consistent with roles that arbitrageurs play in classical finance and in most behavioral finance models. In contrast, our paper shows that short sellers can play a destabilizing role in stock markets. One factor that makes our study different from earlier studies is the inclusion of social media data. Most of the literature on arbitrage and short selling was written before social media had such large presence.

We find that firms that are targeted by short sellers tend to have pump-and-dump patterns in social media tone around the initiation of high short interest. The patterns in social

[13] We regress the number of news stories on firm size, and take the residual. We then sort firms into the two groups based on being above or below the median value of the residual. We do this because large firms tend to have more news stories.

media tone are mirrored by patterns in abnormal stock returns, i.e., stock returns are abnormally high before the initiation of high short interest and abnormally low after, and this effect is stronger for firms that have abnormally positive social media tone before the initiation of high short interest and abnormally negative social media tone after. Our findings suggest that once social media is added to the mix, it may be more profitable for sophisticated investors to manipulate prices and exacerbate mispricing, rather than trade against it. Social media is an increasingly populator form of media and communication, so our findings are relevant for academic theories of price formation, the regulation of social media, the regulation of short sellers, and for how practitioners may view stock price dynamics in the presence of intense social media postings.

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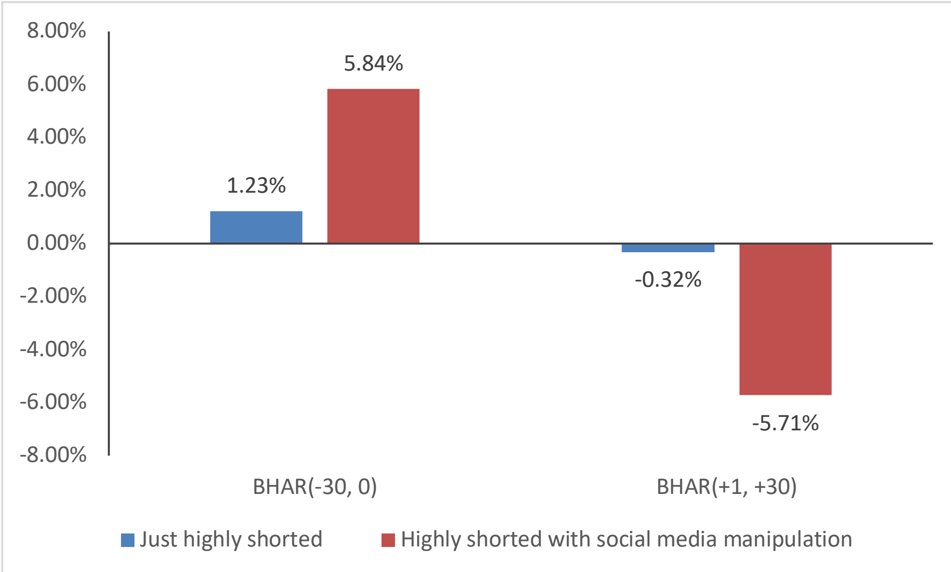
Figure 1: Stock returns before and after highly shorting for stocks with and without social media manipulation



Notes: This figure displays the buy and hold abnormal stock returns (BHAR) before and after the initiation of high short interest. The returns are adjusted by subtracting the return of the value-weighed market portfolio. We divide the highly shorted firms into two groups: with and without social media manipulation. Social media manipulation is defined as having social media tone that is above the sample median before the initiation of high short interest, and below the sample median after the initiation of high short interest.

Table 1
Descriptive Statistics

Variable definitions are provided in the appendix.

	Variable	N	Mean	P50	SD	Min	Max
Social Media Tone	*AVGSMT(-30,0)*	1,125,207	-0.214	-0.222	0.158	-0.551	0.220
	AVGSMT(-5,0)	1,125,207	-0.212	-0.222	0.183	-0.607	0.287
	AVGSMT(+1,+5)	1,125,207	-0.205	-0.215	0.197	-0.631	0.334
	AVGSMT(+1,+30)	1,125,207	-0.210	-0.218	0.129	-0.483	0.159
Traditional Media Tone	*AVGTMT(-30,0)*	1,125,207	0.232	0.000	0.388	-0.750	0.976
	AVGTMT(-5,0)	1,125,207	0.178	0.000	0.360	-0.711	0.975
	AVGTMT(+1,+5)	1,125,207	0.158	0.000	0.346	-0.698	0.974
	AVGTMT(+1,+30)	1,125,207	0.319	0.316	0.399	-0.768	0.975
Short Selling	*SHORT INTEREST*	1,125,207	0.011	0.005	0.016	0.000	0.089
	SHORT INTEREST for the Top 10%	112,509	0.047	0.043	0.023	0.014	0.089
Firm Fundamentals	*SIZE*	1,125,207	23.968	23.827	1.092	22.011	27.337
	ROA	1,125,207	0.041	0.034	0.056	-0.188	0.204
	LEV	1,125,207	0.488	0.498	0.201	0.078	0.894
	BM	1,125,207	0.626	0.619	0.279	0.110	1.209
	PRERET	1,125,207	-0.003	-0.013	0.113	-0.277	0.372
Stock Returns	*BHR(-30, 0)*	1,125,207	0.011	-0.003	0.161	-0.374	0.579
	BHR(-5, 0)	1,125,207	0.002	0.000	0.068	-0.210	0.224
	BHR(+1, +5)	1,125,207	0.002	0.000	0.062	-0.190	0.204
	BHR(+1, +30)	1,125,207	0.008	-0.004	0.156	-0.375	0.555

Table 2
Sample Distribution

Panel A: Year distribution

Year	Freq.	Percent	Cum.
2010	11,695	1.04	1.04
2011	19,083	1.70	2.74
2012	55,059	4.89	7.63
2013	111,460	9.91	17.53
2014	157,961	14.04	31.57
2015	179,890	15.99	47.56
2016	185,667	16.50	64.06
2017	200,084	17.78	81.84
2018	204,308	18.16	100.00
Total	1,125,207	100.00	

Panel B: Industry distribution

Industry	Freq.	Percent	Cum.
Computer and Communications	92,684	8.24	8.24
Pharmaceutical	87,234	7.75	15.99
Real Estate	82,726	7.35	23.34
Chemical Products	52,542	4.67	28.01
Electrical Manufacture	49,850	4.43	32.44
Specialized Equipment Manufacture	46,206	4.11	36.55
Software and Information Technology	41,438	3.68	40.23
Metallic Product Manufacture	39,597	3.52	43.75
Automotive	38,607	3.43	47.18
Construction	36,334	3.23	50.41
Electricity and Heat Supply	34,862	3.10	53.51
Alcoholic Beverage, Non-alcoholic Beverage and Tea	34,151	3.04	56.54
Retails	31,311	2.78	59.33
Coal Mining and Washing	31,121	2.77	62.09
Non-metallic Mineral	30,899	2.75	64.84
Wholesale	30,055	2.67	67.51
General Equipment Manufacture	27,525	2.45	69.96
Non-Ferrous Metal Smelting	22,467	2.00	71.95
Transportation Equipment Manufacture	21,875	1.94	73.90
Ferrous Metal Smelting	18,290	1.63	75.52
Business Service	15,297	1.36	76.88
Water transportation	15,043	1.34	78.22
News and Publishing	15,095	1.34	79.56
Aero Transportation	12,583	1.12	80.68
Internet Service	12,348	1.10	81.78
Food Manufacture	11,508	1.02	82.80
Others	193,559	17.20	100.00
Total	1,125,207	100.00	

Table 3
Short-selling and social media tone

VARIABLES	(1) *AVGSMT(-30,0)*	(2) *AVGSMT(-5,0)*	(3) *AVGSMT(+1,+5)*	(4) *AVGSMT(+1,+30)*
TOP10%SHORT	0.008***	0.009***	-0.005***	-0.009***
	(3.10)	(3.19)	(-3.89)	(-5.45)
AVGTMT	0.017***	0.027***	0.021***	0.015***
	(13.25)	(22.27)	(21.70)	(14.06)
AVGSMT(-30,0)			0.522***	0.395***
			(100.11)	(70.51)
SIZE	0.006	0.007*	0.004*	0.002
	(1.51)	(1.71)	(1.93)	(0.84)
ROA	0.038	0.035	0.016	0.024
	(1.28)	(1.16)	(1.05)	(1.24)
LEV	0.024	0.024	0.008	0.016
	(1.41)	(1.44)	(0.98)	(1.52)
BM	-0.130***	-0.132***	-0.068***	-0.082***
	(-12.24)	(-12.36)	(-12.18)	(-11.54)
PRERET	0.055***	0.041***	0.008***	0.010***
	(13.63)	(9.42)	(2.63)	(2.86)
SOE	-0.009	-0.004	-0.002	-0.007
	(-0.73)	(-0.34)	(-0.31)	(-0.76)
Constant	-0.342***	-0.365***	-0.193***	-0.150**
	(-3.37)	(-3.57)	(-3.65)	(-2.23)
Firm Fixed Effect	Yes	Yes	Yes	Yes
Year/month Fixed Effect	Yes	Yes	Yes	Yes
Observations	1,125,207	1,125,207	1,125,207	1,125,207
Adj-R^2	0.292	0.140	0.208	0.400

Notes: This table examines how social media tone behaves before and after the initiation of high short interest (the top 10% of short interest). *AVGSMT* is the average daily social media tone; *AVGTMT* is the average daily traditional media tone; *TOP10%SHORT* equals 1 if the daily short interest of a firm ranks in the top 10% of short interest (sorted by year) and zero otherwise; short interest is calculated as the daily unbalanced short-selling divided by outstanding shares. Standard errors are adjusted for heteroskedasticity and clustered by firm. t-values are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% levels (two-tail tests), respectively.

Table 4
Short-selling and traditional media tone

VARIABLES	(1) *AVGTMT(-30,0)*	(2) *AVGTMT(-5,0)*	(3) *AVGTMT(+1,+5)*	(4) *AVGTMT(+1,+30)*
TOP10%SHORT	-0.002	0.003	0.004	-0.009*
	(-0.33)	(0.85)	(1.45)	(-1.67)
AVGSMT	0.193***	0.098***	0.074***	0.180***
	(13.12)	(22.12)	(21.69)	(13.18)
AVGTMT(-30,0)			0.051***	0.070***
			(22.56)	(15.09)
SIZE	0.070***	0.049***	0.043***	0.068***
	(6.60)	(7.59)	(7.91)	(6.66)
ROA	0.520***	0.211***	0.142***	0.493***
	(7.24)	(5.34)	(4.25)	(6.98)
LEV	0.052	0.038*	0.025	0.035
	(1.26)	(1.68)	(1.27)	(0.94)
BM	-0.092***	-0.089***	-0.073***	-0.094***
	(-3.36)	(-5.50)	(-5.32)	(-3.67)
PRERET	0.035***	0.032***	0.026***	0.032***
	(2.99)	(5.03)	(4.53)	(2.79)
SOE	0.026	-0.007	-0.007	0.020
	(0.84)	(-0.36)	(-0.42)	(0.67)
Constant	-1.313***	-0.885***	-0.778***	-1.311***
	(-5.13)	(-5.71)	(-5.98)	(-5.41)
Firm Fixed Effect	Yes	Yes	Yes	Yes
Year/month Fixed Effect	Yes	Yes	Yes	Yes
Observations	1,125,207	1,125,207	1,125,207	1,125,207
Adj-R^2	0.211	0.186	0.187	0.217

Notes: This table examines how traditional media tone behaves before and after the initiation of high short interest (the top 10% of short interest). *AVGSMT* is the average daily social media tone; *AVGTMT* is the average daily traditional media tone; *TOP10%SHORT* equals 1 if the daily short interest of a firm ranks in the top 10% of short interest; short interest is calculated as the daily unbalanced short-selling divided by outstanding shares. We control for social media tones over the same window (*AVGSMT*). Standard errors are adjusted for heteroskedasticity and clustered by firm. t-values are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% levels (two-tail tests), respectively.

Table 5
Short-selling in the first week of being listed in pilot program and social media tone

VARIABLES	(1) *AVGSMT(-30,0)*	(2) *AVGSMT(-5,0)*	(3) *AVGSMT(+1,+5)*	(4) *AVGSMT(+1,+30)*
TOP10%SHORT	0.006	-0.024	-0.036**	-0.032***
	(0.52)	(-1.37)	(-2.52)	(-3.00)
AVGTMT	0.019*	0.013	0.039***	0.019**
	(1.89)	(0.92)	(3.17)	(1.98)
AVGSMT(-30,0)			0.585***	0.503***
			(13.04)	(15.15)
SIZE	0.022***	0.026***	0.000	0.006
	(4.50)	(3.66)	(0.04)	(1.15)
ROA	0.240***	0.144	0.052	-0.002
	(2.80)	(1.06)	(0.43)	(-0.02)
LEV	0.044*	0.010	-0.009	-0.007
	(1.67)	(0.26)	(-0.25)	(-0.30)
BM	-0.115***	-0.128***	-0.064**	-0.073***
	(-5.70)	(-4.57)	(-2.44)	(-4.04)
PRERET	0.023	0.094**	0.160***	0.101***
	(0.85)	(2.19)	(3.74)	(3.88)
SOE	0.022***	0.022*	0.018	0.011
	(2.72)	(1.86)	(1.55)	(1.40)
Constant	-0.726***	-0.802***	-0.053	-0.184*
	(-6.78)	(-5.16)	(-0.35)	(-1.68)
Observations	3,736	3,736	3,736	3,736
Adj-R^2	0.092	0.041	0.155	0.277

Notes: This table examines social media tone before and after the initiation of high short interest (the top 10% of short interest) during the first week that a firm is in the shorting program. The sample consists of firm-day observations and is limited to the first five days when a firm is in the shorting program. *AVGSMT* is the average daily social media tone; *AVGTMT* is the average daily traditional media tone; *TOP10%SHORT* equals 1 if the daily short interest of a firm ranks in the top 10% of short interest; short interest is calculated as the daily unbalanced short-selling divided by outstanding shares. We control for traditional media tones over the same window (*AVGTMT*). Standard errors are adjusted for heteroskedasticity and clustered by firm. t-values are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% levels (two-tail tests), respectively.

Table 6
Short-selling in the first week of being listed in pilot program and traditional media tone

VARIABLES	(1) *AVGTMT(-30,0)*	(2) *AVGTMT(-5,0)*	(3) *AVGTMT(+1,+5)*	(4) *AVGTMT(+1,+30)*
TOP10%SHORT	0.038	0.052	0.022	-0.005
	(1.27)	(1.55)	(0.67)	(-0.16)
AVGSMT	0.198*	0.050	0.150***	0.205**
	(1.89)	(0.92)	(3.60)	(2.09)
AVGTMT(-30,0)			0.067***	0.123***
			(2.62)	(3.48)
SIZE	0.011	0.079***	0.090***	0.058***
	(0.70)	(5.63)	(7.10)	(4.12)
ROA	0.174	-0.288	-0.167	0.250
	(0.57)	(-1.08)	(-0.73)	(0.88)
LEV	0.136	-0.095	-0.108*	-0.069
	(1.59)	(-1.26)	(-1.73)	(-0.81)
BM	-0.093	0.018	-0.005	-0.013
	(-1.46)	(0.34)	(-0.11)	(-0.20)
PRERET	0.122	0.178**	-0.128*	-0.110
	(1.36)	(2.19)	(-1.75)	(-1.22)
SOE	0.009	0.004	-0.010	-0.001
	(0.33)	(0.20)	(-0.51)	(-0.03)
Constant	0.092	-1.619***	-1.858***	-0.990***
	(0.26)	(-5.35)	(-6.72)	(-3.20)
Observations	3,736	3,736	3,736	3,736
Adj-R^2	0.013	0.036	0.059	0.043

Notes: This table examines traditional media tone before and after the initiation of high short interest (the top 10% of short interest) during the first week that a firm is in the shorting program. The sample consists of firm-day observations, but is limited to the first five days that a firm is in the shorting program. *AVGSMT* is the average daily social media tone; *AVGTMT* is the average daily traditional media tone; *TOP10%SHORT* equals 1 if the daily short interest of a firm ranks in the top 10% of short interest; short interest is calculated as the daily unbalanced short-selling divided by outstanding shares. We control for social media tone over the same window (*AVGSMT*). Standard errors are adjusted for heteroskedasticity and clustered by firm. t-values are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% levels (two-tail tests), respectively.

Table 7
Short-selling pilot program and the number of social media posts and volatility of social media tone

	Whole sample		Short-selling sample	
VARIABLES	*POSTNUM*	*SD SMTONE*	*POSTNUM*	*SD SMTONE*
	(1)	(2)	(3)	(4)
SHORT	0.084***	0.003***		
	(4.16)	(4.40)		
CLOSEWINDOW			-0.131***	-0.004***
			(-9.73)	(-4.79)
SIZE	0.190***	0.003***	0.159***	0.006***
	(11.36)	(5.84)	(4.57)	(4.87)
ROA	-0.425***	0.0167***	-0.041	0.019**
	(-4.35)	(5.07)	(-0.21)	(2.49)
LEV	0.095*	0.003	-0.013	-0.007
	(1.73)	(1.56)	(-0.11)	(-1.63)
BM	0.245***	-0.005***	0.045	-0.014***
	(4.83)	(-3.52)	(0.47)	(-4.05)
RETURN	-0.205***	0.000	-0.211***	-0.003***
	(-17.84)	(0.94)	(-10.41)	(-3.77)
SDAR	35.900***	0.520***	30.660***	0.681***
	(148.70)	(32.34)	(64.64)	(22.65)
POSTNUM		-0.048***		-0.058***
		(-160.99)		(-105.06)
Constant	0.285	0.535***	1.891**	0.514***
	(0.76)	(49.14)	(2.29)	(17.31)
Firm Fixed Effect	YES	YES	YES	YES
Year/month Fixed Effect	YES	YES	YES	YES
Observations	249,963	249,963	56,982	56,982
Adj-R^2	0.564	0.447	0.605	0.518

Notes: This table examines how short selling affects the number of social media posts and the volatility of social media tone. Columns (1) and (2) use all firm-month observations for all firms in our sample. Columns (3) and (4) only include firms that can be shorted. *POSTNUM* is the log value of one plus number of social media posts in a month; *SD SMTONE* is the monthly standard deviation of daily social media tone; *SHORT* equals 1 after a firm is listed in the pilot program, and 0 otherwise (firms may be removed out of the list, for these firms, *SHORT* equals 0 after they are excluded); *CLOSEWINDOW* equals 1 for the period when short selling was temporarily suspended in China (from 2015, Aug. to 2016 Mar.), and 0 for other periods. Standard errors are adjusted for heteroskedasticity and clustered by firm. t-values are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% levels (two-tail tests), respectively.

Table 8
Short-selling pilot program and the number of news articles and the volatility of traditional media tone

	Whole sample		Short-selling sample	
VARIABLES	*ARTICLENUM*	*SD TMTONE*	*ARTICLENUM*	*SD TMTONE*
	(1)	(2)	(3)	(4)
SHORT	-0.001	-0.001		
	(-0.06)	(-0.38)		
CLOSEWINDOW			0.006	0.021***
			(0.41)	(3.83)
SIZE	0.232***	-0.001	0.289***	0.001
	(14.48)	(-0.24)	(7.59)	(0.08)
ROA	-0.196**	-0.086***	-0.157	-0.140**
	(-2.12)	(-3.24)	(-0.70)	(-2.23)
LEV	0.086*	-0.022*	0.078	-0.015
	(1.72)	(-1.83)	(0.59)	(-0.51)
BM	-0.296***	0.034***	-0.314***	0.028
	(-6.75)	(3.27)	(-3.22)	(1.36)
RETURN	-0.105***	-0.011***	-0.119***	-0.010**
	(-9.68)	(-3.98)	(-6.42)	(-2.46)
SDAR	15.510***	1.263***	16.780***	1.095***
	(50.92)	(13.34)	(31.36)	(6.37)
ARTICLENUM		-0.005***		-0.009***
		(-2.73)		(-3.32)
Constant	-3.490***	0.420***	-4.421***	0.410**
	(-9.56)	(5.74)	(-4.80)	(2.28)
Firm Fixed Effect	YES	YES	YES	YES
Year/month Fixed Effect	YES	YES	YES	YES
Observations	82,842	82,842	26,254	26,254
Adj-R^2	0.627	0.062	0.742	0.101

Notes: This table examines how short selling affects the number of news articles and the volatility of traditional media tone. Column (1) and (2) use all firm-month observations. Column (3) and (4) only include firms that can be shorted. *ARTICLENUM* is the log value of one plus the number of news articles in traditional media; *SDTMTONE* is the monthly standard deviation of daily traditional media tone; *SHORT* equals 1 if a firm is in the shortable, and 0 otherwise; *CLOSEWINDOW* equals 1 for the period when short selling was temporarily suspended in China (from 2015, Aug. to 2016 Mar.), and 0 for other periods. Standard errors are adjusted for heteroskedasticity and clustered by firm. t-values are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% levels (two-tail tests), respectively.

Table 9 (Panel A)
Determinants of firm's being highly shorted and manipulated via social media

	(1)	(2)
VARIABLES	*TARGET1_SHORT*	*TARGET2_SHORT*
ACTIVEUSERS	32.840***	8.043***
	(9.509)	(7.727)
NONACTIVE	1.297*	0.515**
	(1.766)	(2.512)
LAW	-0.163***	-0.171***
	(-3.024)	(-3.002)
INST	3.410***	3.364***
	(5.148)	(4.704)
ANALYST	0.003	-0.005
	(0.059)	(-0.107)
ILLIQUID	-41.458***	-40.696***
	(-5.954)	(-5.496)
SIZE	0.094	0.072
	(1.371)	(0.971)
ROA	-1.353	-1.313
	(-1.233)	(-1.104)
LEV	0.493	0.478
	(1.358)	(1.429)
BM	-1.458***	-1.508***
	(-4.721)	(-5.336)
RET	-0.329***	-0.300***
	(-3.714)	(-3.221)
SOE	0.148	0.205**
	(1.470)	(2.037)
Constant	-5.607***	-5.459***
	(-4.544)	(-4.097)
Industry Fixed Effects	Yes	Yes
Year/month Fixed Effect	Yes	Yes
Observations	1,098,185	1,093,297
Pseudo R^2	0.054	0.063

Table 9 (Panel B)

VARIABLES	(1) *TARGET1_SHORT*	(2) *TARGET2_SHORT*
ACTIVE/NONACTIVE	0.720***	1.261***
	(6.094)	(6.076)
LAW	-0.168***	-0.179***
	(-3.118)	(-3.165)
INST	3.359***	3.260***
	(5.112)	(4.649)
ANALYST	0.013	0.012
	(0.238)	(0.246)
ILLIQUID	-37.410***	-33.488***
	(-5.737)	(-5.058)
SIZE	0.125*	0.124*
	(1.864)	(1.782)
ROA	-1.308	-1.182
	(-1.193)	(-1.006)
LEV	0.500	0.487
	(1.379)	(1.469)
BM	-1.458***	-1.486***
	(-4.702)	(-5.234)
RET	-0.291***	-0.241***
	(-3.333)	(-2.646)
SOE	0.136	0.183*
	(1.355)	(1.837)
Constant	-6.213***	-6.486***
	(-5.204)	(-5.177)
Industry Fixed Effects	Yes	Yes
Year/month Fixed Effect	Yes	Yes
Observations	1,098,185	1,093,297
Pseudo R^2	0.049	0.054

Notes: This table examines the determinants of firm's being highly shorted and having social media manipulation. *TARGET1_SHORT* (*TARGET2_SHORT*) equals 1 if a firm is highly shorted and has social media tone that is above (below) the sample median before (after) the day short interest is measured. We measure social media tone over 5-day (30-day) periods in column 1 (column 2). *ACTIVEUSERS* is the number of posts over the measurement window (5 days or 30 days) from active users scaled by the number of total posts over the prior year. *NONACTIVE* is total posts minus the number of posts from active users scaled by the number of total posts over the prior year. *LAW* measures the provincial legal environment where the firm is located; *LAW* equals 3 for the highest tertile (more law and order), 2 for the middle tertile, and 1 for the lowest tertile. *INST* is the institutional shareholding of the firm. *ANALYST* is the log of the number of analyst following of the firm. *ILLIQUID* measures the stock liquidity, which is constructed following Amihud (2002). *SOE* equals one for state-owned firms, and zero otherwise. We also control firm size (SIZE), return on assets (ROA), leverage (LEV), book-to-market ratio (BM), and past yearly stock return (RET). All of these firm characteristics are lagged. Standard errors are robust and clustered by firm. z-values are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% levels (two-tail tests), respectively.

Table 10
Short Selling, Social Media Tone, Stock Returns and Volume

Panel A: Short Selling, Social Media Tone, and Stock Returns

	(1)	(2)	(3)	(4)
VARIABLES	*BHR(-30, 0)*	*BHR(-5, 0)*	*BHR(+1, +5)*	*BHR(+1, +30)*
TOP10%SHORT$\times$MANIPULATE	0.007*	0.002**	-0.004***	-0.006**
	(1.95)	(2.18)	(-7.18)	(-2.45)
TOP10%SHORT	0.018***	0.004***	-0.003***	-0.017***
	(8.31)	(9.47)	(-7.41)	(-8.61)
MANIPULATE	0.042***	0.012***	-0.014***	-0.046***
	(34.32)	(44.80)	(-66.88)	(-46.59)
SIZE	0.009***	0.002***	0.001***	0.008***
	(16.04)	(14.86)	(14.05)	(14.49)
ROA	0.046***	0.008**	0.008***	0.071***
	(2.67)	(2.38)	(2.77)	(4.41)
LEV	0.030***	0.006***	0.004***	0.028***
	(7.82)	(7.98)	(7.11)	(7.68)
BM	-0.065***	-0.012***	-0.011***	-0.057***
	(-20.24)	(-19.51)	(-20.64)	(-19.05)
EP	0.078***	0.016***	0.010***	0.044***
	(6.48)	(6.69)	(5.28)	(3.88)
PRERET	-0.079***	-0.007***	-0.003***	-0.032***
	(-16.70)	(-7.03)	(-3.86)	(-7.23)
SOE	0.003**	0.001***	0.001***	0.003**
	(2.46)	(3.40)	(3.01)	(2.45)
Constant	-0.193***	-0.036***	-0.025***	-0.164***
	(-15.71)	(-15.02)	(-11.59)	(-13.16)
Day Fixed Effects	Yes	Yes	Yes	Yes
Observations	1,125,207	1,125,207	1,125,207	1,125,207
Adj-R^2	0.470	0.427	0.435	0.476

Table 10 Cont.
Panel B: Short Selling, Social Media Tone, and Trading Volume

VARIABLES	(1) *VOL(-30, 0)*	(2) *VOL(-5, 0)*	(3) *VOL(+1, +5)*	(4) *VOL(+1, +30)*
TOP10%SHORT×MANIPULATE	0.020*	0.004***	0.003***	0.021*
	(1.84)	(3.25)	(2.64)	(1.66)
TOP10%SHORT	0.130***	0.028***	0.022***	0.087***
	(8.87)	(9.65)	(9.24)	(5.74)
MANIPULATE	0.016***	0.002***	0.002***	0.034***
	(5.82)	(6.46)	(8.64)	(10.49)
SIZE	0.018	0.007	0.007	0.040
	(0.71)	(1.42)	(1.61)	(1.43)
ROA	-0.788***	-0.157***	-0.133***	-1.034***
	(-3.62)	(-3.74)	(-3.83)	(-4.34)
LEV	0.024	0.007	0.006	0.020
	(0.26)	(0.38)	(0.44)	(0.21)
BM	-0.709***	-0.152***	-0.130***	-0.756***
	(-10.81)	(-11.78)	(-12.11)	(-10.31)
EP	0.846***	0.160***	0.132***	0.861***
	(5.82)	(5.66)	(5.61)	(5.39)
PRERET	0.775***	0.361***	0.342***	0.938***
	(34.47)	(48.10)	(49.63)	(29.33)
SOE	0.010	0.003	0.003	0.022
	(0.19)	(0.33)	(0.38)	(0.41)
Constant	0.578	0.032	0.009	0.047
	(0.94)	(0.26)	(0.08)	(0.07)
Day Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Observations	1,125,207	1,125,207	1,125,207	1,125,207
Adj-R2	0.643	0.568	0.562	0.617

Notes: This table examines stock returns for highly shorted firms, firms that are likely to have manipulated social media (MANIPULATE = 1), and the interaction between the two variables. *VOL* is cumulative daily volume over the measurement period (5 or 30 days), where daily volume is calculated as shares traded scaled by shares outstanding. *BHR* is buy-and-hold stock returns. *MANIPULATE* equals 1 if social media tone is larger than the sample median in the pre window and smaller than the sample median in the post window, and 0 otherwise. We define *MANIPULATE* using the same window as the stock return or volume window (5 days or 30 days). *TOP10%SHORT* equals 1 if the daily short interest of a firm ranks in the top 10% of short interest; *SHORT INTEREST* is calculated as the daily unbalanced short-selling divided by outstanding shares. Standard errors are robust and clustered by firm. t-values are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% levels (two-tail tests), respectively.

Table 11
Short Selling, Social Media Tone, and Stock Returns: The Effects of News Events

	BHR(+1, +30)			
VARIABLES	*News event$_t$=1*	*News event$_t$=0*	More news during (+1,+30)	Less news during (+1,+30)
	(1)	(2)	(3)	(4)
SHORT×MANIPULATE	-0.004	-0.006**	-0.004	-0.009***
	(-1.23)	(-2.28)	(-1.14)	(-2.79)
TOP10%SHORT	-0.014***	-0.017***	-0.015***	-0.019***
	(-5.03)	(-8.35)	(-5.23)	(-7.59)
MANIPULATE	-0.054***	-0.044***	-0.047***	-0.043***
	(-30.35)	(-44.13)	(-32.11)	(-35.32)
SIZE	0.008***	0.009***	0.010***	0.009***
	(8.62)	(15.24)	(9.18)	(11.05)
ROA	0.076***	0.068***	0.064***	0.097***
	(2.69)	(4.18)	(2.87)	(3.64)
LEV	0.036***	0.025***	0.031***	0.029***
	(5.02)	(7.01)	(5.84)	(5.34)
BM	-0.052***	-0.059***	-0.055***	-0.055***
	(-9.43)	(-19.33)	(-12.43)	(-12.36)
EP	0.005	0.053***	0.051**	0.033**
	(0.28)	(4.43)	(2.45)	(2.38)
PRERET	-0.024***	-0.033***	-0.037***	-0.033***
	(-3.21)	(-7.51)	(-5.90)	(-5.89)
SOE	0.001	0.003***	0.004***	0.000
	(0.29)	(2.82)	(2.83)	(0.12)
Constant	-0.177***	-0.188***	-0.210***	-0.199***
	(-8.15)	(-13.95)	(-8.52)	(-9.91)
Day Fixed Effects	Yes	Yes	Yes	Yes
Observations	196,404	928,803	549517	549496
Adj-R^2	0.426	0.491	0.459	0.525

Notes: This table examines whether highly shorted firms with pump-and-dump patterns in social media tone are more likely to have low returns on news days. The dependent variable is the buy-and-hold raw stock return over 30 days. We define news events as articles published in all the traditional media. *News event$_t$* equals one for days with news events, and zero otherwise. In columns 3 and 4 we count the number of news events over the window of (+1, +30), adjust for firm size, and then divide the whole sample into two groups based on the sample median (column 3 and 4). *MANIPULATE* equals 1 if the average social media tone (*AVGSMT*) in the prior window is larger than the sample median, and *AVGSMT* in the post window is smaller than the sample median, and 0 otherwise. We define *MANIPULATE* using the same window as that for the return window. *%SHORT* equals 1 if the daily short interest of a firm ranks in the top 10% of short interest. All the standard errors are adjusted for heteroskedasticity and clustered by firm. t-values are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% levels (two-tail tests), respectively.

Appendix
Variable definition

Variables	Definition
SHORT INTEREST	= daily unbalanced short-selling divided by outstanding shares
TOP10%SHORT	= 1 for the top 10% of short interest; = 0 otherwise
AVGSMT(-30 , 0)	= the average daily social media tone over the period t-30 to t, with missing value replaced by zero
AVGSMT(-5 , 0)	= the average daily social media tone over the period t-5 to t, with missing value replaced by zero
AVGSMT(+1 , +5)	= the average daily social media tone over the period t+1 to t+5, with missing value replaced by zero
AVGSMT(+1 , +30)	= the average daily social media tone over the period t+1 to t+30, with missing value replaced by zero
AVGTMT(-30 , 0)	= the average daily traditional media tone over the period t-30 to t, with missing value replaced by zero
AVGTMT(-5 , 0)	= the average daily traditional media tone over the period t-5 to t, with missing value replaced by zero
AVGTMT(+1 , +5)	= the average daily traditional media tone over the period t+1 to t+5, with missing value replaced by zero
AVGTMT(+1 , +30)	= the average daily traditional media tone over the period t+1 to t+30, with missing value replaced by zero
SIZE	= the log value of the market value of firms at the end of the fiscal year
LEV	= the leverage ratio at the end of the fiscal year, which is calculated as total debt divided by total assets
ROA	= return on total assets, which is net income divided by total assets
BM	= book-to-market ratio at the end of the fiscal year
PRERET	= 30-day cumulative size-adjusted abnormal returns prior to shorting days (skip 1 month, that is, from day t-60 to day t-30)
SD SMTONE	= the monthly standard deviation of daily social media tone
SD TMTONE	= the monthly standard deviation of daily traditional media tone
SHORT	= 1 if a firm is in the short list pilot program, = 0 if not

CLOSEWINDOW	= 1 for the period that most of the security firms temporarily close their business of lending stocks to the market (2015, Aug. to 2016 Mar.), = 0 for other periods
RET	= stock return over the fiscal year
SDAR	= the monthly standard deviation of stock return
POSTNUM	= the intensity of social media posts for a firm in a month, which is measured as the log value of one plus number of social media posts in a month
ARTICLENUM	= the coverage intensity of traditional media news articles for a firm in a month, which is measured as the log value of one plus number of articles in traditional media in a month
TARGET1_SHORT	= 1 if a firm is highly shorted and has social media tone over 5-day periods that is above (below) the sample median before (after) the day short interest is measured
TARGET2_SHORT	= 1 if a firm is highly shorted and has social media tone over 30-day periods that is above (below) the sample median before (after) the day short interest is measured
MANIPULATE	=1 if the firm has social media tone above the sample media in the pre-window and below the sample median in the post window; =0 otherwise
BHR(-30, 0)	= buy-and-hold raw stock returns over the period of t-30 to t
BHR(-5, 0)	= buy-and-hold raw stock returns over the period of t-5 to t
BHR(+1, +5)	= buy-and-hold raw stock returns over the period of t+1 to t+5
BHR(+1, +30)	= buy-and-hold raw stock returns over the period of t+1 to t+30
VOL(-30, 0)	= cumulative stock volume over the period of t-30 to t, where daily stock volume is calculated as firms' daily percentage of shares traded
VOL(-5, 0)	= cumulative stock volume over the period of t-5 to t, where daily stock volume is calculated as firms' daily percentage of shares traded
VOL(+1, +5)	= cumulative stock volume over the period of t+1 to t+5, where daily stock volume is calculated as firms' daily percentage of shares traded
VOL(+1, +30)	= cumulative stock volume over the period of t+1 to t+30, where daily stock volume is calculated as firms' daily percentage of shares traded
EP	= the ratio of earnings to the market value of the firm at the end of the fiscal year, where earnings is net income excluding nonrecurrent gains and losses

ACTIVEUSERS	= the number of posts from active users scaled by the number of total posts over the prior year
NONACTIVE	= total posts minus the number of posts from active users scaled by the number of total posts over the prior year
LAW	= the law environment index where the firm locates, which equals 3 for the highest tertile, 2 for the middle tertile and 1 for the lowest tertile
INST	= the institutional shareholding of the firm
ANALYST	= the log of the number of analyst following of the firm
ILLIQUID	= stock liquidity, which is the average of daily Amihud's (2002) liquidity measure (calculated as the absolute value of stock return divided by dollar trading volume on a given day)