Are Daytime and Overnight Sentiments Different?*

Yubin Li†
Harbin Institute of Technology, Shenzhen

Xin Liu‡
Peking University HSBC Business School

Ke Peng§
Harbin Institute of Technology, Shenzhen

Zhaodong (Ken) Zhong**
Rutgers University

*Li acknowledges financial support from the National Natural Science Foundation of China (Grant No. 72002059), the Shenzhen Peacock Plan research fund (Grant No. GA11409006), the Shenzhen Key Research Base of Humanities and Social Sciences (Grant No. KP191002). Peng acknowledges financial support from the Shenzhen Key Research Base on Humanities and Social Science (Grant No. KP191003) and the Natural Science Foundation of Shenzhen (Grant No. GXWD20201230155427003-20200824124438001). Zhong acknowledges financial support from the David Whitcomb Center for Research in Financial Services at Rutgers Business School.
†Address: School of Economics and Management, Harbin Institute of Technology, Shenzhen, China, 518055; Email: liyubin@hit.edu.cn.
‡ Address: HSBC Business School, Peking University, Shenzhen, China, 518055; Email: xinliu@pku.edu.cn
§ Address: School of Economics and Management, Harbin Institute of Technology, Shenzhen, China, 518055; Email: k.peng@hit.edu.cn.
** Address: Department of Finance, Rutgers University, 100 Rockafeller Road, Piscataway, NJ 08854; Email: zdzhong@business.rutgers.edu

Are Daytime and Overnight Sentiments Different?

Abstract

This study compares retail investors' daytime and overnight firm-specific sentiments. The sentiment measures are textually extracted from China's most popular platform for retail investors. We find that both daytime and overnight sentiments positively predict short-term daily returns, especially for posts with stronger influence or wider dissemination. However, whereas the positive predictability of overnight sentiment reverses in the long run, the positive predictability of daytime sentiment persists for up to 6 months. Consistent with clientele heterogeneity, only daytime sentiment can predict future earnings surprises, implying that it contains fundamental information, but overnight sentiment is dominated by irrational moods. A hedging portfolio based on the daytime (overnight) sentiment generates an annualized return of 35.3% (-11.9%) and a Sharpe ratio of 3.06 (-1.26) after accounting for a round-trip commission cost of 0.02%.

Keywords: **sentiment, individual investors, intraday and overnight**
JEL classification: G10, G24, M40

1. Introduction

A large body of literature has explored the impact of investor sentiment on stock markets. A seminal paper by De Long et al. (1990) theoretically establishes that noise traders' speculative sentiment drives stock prices from their essential values. Recent studies focus on firm-specific investor sentiment and quantitatively or textually derive it from online platforms such as Google, Twitter, and StockTwits (Tumarkin and Whitelaw 2001; Antweiler and Frank 2004; Das and Chen 2007; Sabherwal et al. 2011; Chen et al. 2014; Leung and Ton 2015; Da et al. 2011, 2015; Bollen et al. 2011; Yang et al. 2015; Oliveira et al. 2017). Some of these studies have also explored high-frequency intraday sentiments (Sibley et al. 2016; Sun et al. 2016; Renault 2017; Behrendt and Schmidt 2018). Intuitively, we believe that different agents are active during different time periods, simply because they tend to trade at different times. Just as argued by Lou et al. (2019), "*Some investors may prefer to trade at or near the morning open while others may prefer to trade during the rest of the day up to and including the market close. These two periods-when the market is open vs. when it is closed differ along several key dimensions, including information flow, price impact, and borrowing costs*". They also confirm that institutions tend to initiate trades throughout the day and particularly at the close while the opposing clientele (individuals) are more likely to initiate trades near the open. However, given this clientele heterogeneity, few studies break down firm-specific daily sentiment and systematically compare retail investors' daytime and overnight sentiments. Based on novel high-frequency textual data from the largest online retail investor community in China, we try to fill this research gap.

Empirically, our stock sample includes all China A-share stocks from January 2016 to December 2020. The firm-specific high-frequency measure of retail sentiment was extracted from more than

29 million posts on Xuqiu (the Chinese version of StockTwits). Every post was processed with machine learning and natural language processing techniques, and a quantitative sentiment score was assigned. We calculated an aggregate score for each stock over every intraday and overnight period. Xueqiu allows users to follow stocks, view real-time quotes, and exchange, as well as discuss investment insights, open stock accounts, and trade stocks in real time. Thus, most users in this community are actual market participants instead of spectators, and the sentiment measure here is cleaner than its counterparts extracted from Twitter or Weibo (the Chinese version of Twitter), given that the users on these online platforms may not be actual investors. In addition, since professionals such as analysts or mutual fund managers are not allowed to post on Xueqiu, this setting introduces a cleaner measure of individual investor sentiment.

Our empirical work proceeds through several steps. First, we confirm the validity of our sentiment measure based on Chinese textual analyses. Abody et al. (2018) propose using overnight returns as a retail sentiment proxy, given that sentiment-driven retail investors with limited attention prefer trading in the open market (Berkman et al. 2012). We confirm that our overnight sentiment index covaries with overnight returns that have strong economic significance, consistent with the notion that higher overnight retail sentiment pushes the open-market price upward. Similarly, our daytime sentiment measure aslo comove with the intraday return. Again following Abody et al. (2018), we show that both our daytime and overnight sentiment measures present short-term persistence patterns with strong positive time-series autocorrelations. Our measure of daytime sentiment also positively correlates with contemporaneous intraday volatility, which is consistent with previous findings (Behrendt and Schmidt 2018). It also comoves with stock turnover, directly lending further support to previous research that uses stock turnover to positively measure sentiment

(Baker et al. 2012; Wang et al. 2022). And we construct the conformity measure of sentiment and find that it is negatively correlated with trading volume, stock turnover, and intraday volatility, which is consistent with previous literature and again affirms the validity of our sentiment measures (Antweiler and Frank, 2004; Leung and Ton, 2015; Al-Nasseri and Ali, 2018).

Second, we compare daytime and overnight sentiments. Since the overnight interval (3:00 p.m.–9:00 a.m.) is three times as long as the daytime interval (9:00 a.m.–3:00 p.m.), posts are much more voluminous during the overnight period. More notably, overnight sentiment is 90% more positive than daytime sentiment (0.575 vs. 0.302), implying a much stronger optimism of individual investors during the night. The conformity measure is also 25% higher during the overnight period (0.46 vs. 0.37), indicating a smaller belief dispersion and a stronger herding. These striking differences suggest the striking clientele heterogeneity in different time periods. Specifically, during the daytime, most individual investors are doing their full-time jobs and posting little on social media, but individual professional arbitrageurs are still focusing on stocks and remain active in the online community, thus dominating the daytime sentiment. And their daytime sentiment is simultaneously adjusted by real-time trading, which contains valuable information. In contrast, during the night, most noise individual investors become active and dominate the overnight sentiment. Therefore, we conjecture that the daytime sentiment could be more informative due to more serious trading by individual arbitrageurs. This is also consistent with Lou et al. (2019) and Akbas et al. (2022), who find an intense daily tug of war between opposing investor clienteles: noise traders overnight and arbitrageurs during the day.

Next, based on this conjecture, we compare the return predictability of daytime and overnight sentiments. In the short term, the daytime sentiment positively predicts both close-to-close and open-to-open daily returns. Economically, one standard deviation increase in daytime retail sentiment leads to a 9.16 (4.56) bps increase in the following close-to-close (open-to-open) return, which is 31% (19%) of the sample mean. This is also practically profitable given that the institutional round-trip trading commission is between 1 and 3 bps in China. The predictive power is robust in addition to other factors, firm, and day fixed effects. However, overnight sentiment only predicts the following open-to-open daily returns and has no predictability for the following close-to-close daily returns. The economic significance is also weaker, with one standard deviation increase in overnight sentiment moving the 2.45 bps increase in the open-to-open return, which is only comparable to the commissions. In the long term, daytime sentiment can positively predict the following close-to-close return for up to 6 months without any reversal. However, the predictability of overnight sentiment starts to reverse on the second day and even become a significant negative indicator of open-to-open return from 1 week to 6 months afterwards. These results lead us to naturally believe that the daytime sentiment contains valuable fundamental information, while the overnight sentiment is a contrarian indicator overwhelmed by noise. Thus, we use daytime and overnight sentiment to predict earnings surprises, which serve as proxies for fundamental information. The analyses show that daytime sentiment can positively predict subsequent earnings surprises in both the 3-month and the 6-month windows, while overnight sentiment shows no predictability. Taken together, these striking comparisons support our hypothesis that daytime sentiment contains valuable fundamental information, while overnight sentiment is more likely to be driven by emotions and only creates a temporary demand shock. More importantly, these results imply that previous findings of the full day sentiment being a negative predictor of future returns could be mainly driven by overnight sentiment (Fisher and

Statman 2000; Ding et al. 2018).

Quite few sentiment studies based on social media have noticed the role of dissemination power. But as well-known, those big social media accounts with high influence and strong dissemination power can affect the capital market fluctuation and even political agenda such as Presidential Elections. Thus, we then examine the effects of the post-specific dissemination power on sentiment predictability. To our knowledge, this is the first study to do so based on the rich metrics of our textual data. Empirically, the dissemination power of a post is defined from several dimensions: the number of likes, the number of retweets, the number of favorites, the number of replies, and the number of account followers. When a post provides more insightful interpretations of public information or directly provides private information, it can attract more attention, gains more likes, and is distributed more quickly and widely. We find that the covariation between daytime (overnight) sentiments and contemporaneous return is stronger for posts with wider dissemination. We also find that the daytime sentiment has stronger positive predictability for both short-term and long-term return if it is extracted from relatively high-quality posts with wider dissemination. On the contrary, the overnight sentiment extracted from low-quality posts is a clearer contrary indicator of future return in both the short and long term. Accordingly, these findings suggests that, for the future research, the post-specific dissemination feature should be a key factor in analyzing social media sentiments.

Lastly, to explore practical implications, we build a long-short strategy based on the positive short-term predictability of sentiment-based measures. The investment period we use is from 2016/01/01 to 2020/12/31. And we construct 7 sentiment-based stock filters, i.e., the level of daytime sentiment, the level of overnight sentiment, the level of full day sentiment, the daily change in daytime sentiment, the daily change in overnight sentiment, the daily change in full day sentiment, and the difference between daytime and overnight sentiment. First, we find that for most sentiment-based predictors, the market close-to-close trading strategies are superior to the market open-to-open trading strategies. For example, for the level of daytime sentiment, the annualized return of close-to-close trading strategy is 35.3% after the round-trip commission costs of 0.02%, but it decreases to -1.12% for the open-to-open strategy. This suggests that trading at the market opening is not an optimal decision when individual investors are crowding. Second, we compare the efficiency of sentiment level and the change in sentiment. Most previous studies have focused on the change in sentiment that can generate significant abnormal returns (Lee et al. 1991; Han 2008; Kurov 2010). However, we find that the level of sentiment produces higher annualized returns and Sharpe ratios. For example, the close-to-close trading portfolio based on the daily sentiment level produces an annualized return of 43.6%, while the counterpart portfolio based on the change in daily sentiment only generates 20.3% in annualized returns. Third, the tug of war measure of individual sentiment (the difference between daytime and overnight sentiment) performs quite well and generate an annualized return of 25.7% accounting for the commissions costs of 0.02%. And when the trading commission is relatively low, it even generates the highest Sharpe ratio and shows the best risk-return trade-off. Taken together, these findings suggests that our measure of individual sentiment is also applicable to practitioners.

This study mainly contributes to two research streams. First, our study is related to the “tug of war” noted in the literature: recent work suggests that individual and institutional investors represent two investor clienteles who cause persistent opposing price pressures during the respective overnight and daytime trading periods. According to Lou et al. (2019), two distinct clienteles tend to dominate the overnight and daytime trading sessions, and persistent excess demand by these respective groups of investors can create a daily "tug of war." The same study finds that individual investors are inclined to initiate trades overnight and near the market's opening, while institutional investors are likely to trade in the opposite direction throughout the daytime. Berkman, Koch, Tuttle, and Zhang (2012) also find evidence suggesting that overnight buying by individual investors tends to cause upward price pressure at the market open that is reversed during the day, presumably by institutional trading. Consistently, based on textual analysis, our findings also confirm this "tug of war" from the perspective of social media sentiment, and our research also provides further international market evidence.

Second, we provide further evidence on the debate of whether investor sentiment contains valuable information or just reflects irrational trader moods. One strand of the literature argues that sentiment is more likely to be uninformative, only reflecting individual and often irrational moods, which creates overreaction or underreaction and then a long-term reversal. For example, Fisher and Statman (2000) demonstrate that small-cap investor sentiment is "a reliable contrary indicator of future S&P 500 returns". Brown and Cliff (2005) find a negative correlation between investor sentiment and Dow Jones Industrial Average returns over the next 1 to 3 years. Baker and Wurgler (2006) also show that small, young, and distressed stocks are affected more by the cross-sectional effect of investor sentiment (see also Kumar and Lee 2006; Lemmon and Portniaguina 2006; Qiu and Welch 2006; Schmeling 2009; Joseph et al. 2011; Bredin 2013; and Ding et al. 2018; Wang et al. 2021). However, another strand of literature finds that investment sentiment contains valuable information. For example, Sprenger et al. (2014) argue that the most recent information for all stocks is disseminated on Twitter. Chen et al. (2014) find that information from Seeking Alpha can predict earnings. Da et al. (2015) show that the Google search index can predict stock returns because it contains more timely information than the concurrent market price. James et al. (2016) show that an online platform's crowdsourced earnings estimates can predict actual earnings. Bartov et al. (2018) find that aggregate sentiment from Twitter can predict companies' earnings surprises. Our study extends previous literature by exploring the clientele features of sentiment from trading sessions and finds that daytime sentiment generally contains valuable information, but overnight sentiment is generally noise. Specially, we also explore this issue from the dissemination features of social media posts and provide more details. To some extent, our findings could help to reconcile the opposing arguments of this debate.

The remainder of this paper is organized as follows. Section 2 discusses the data and the methodology used. Section 3 reports the summary statistics. The major empirical results are presented in Section 4. Section 5 provides additional analyses and Section 6 concludes the paper.

2. Data and Methodology

Our China A-share market sample spans from January 2016 to December 2020, covering a part of the COVID-19 pandemic period. We augment these data with information from the China Stock Market and Accounting Research Database (CSMAR). To break down the close-to-close return into overnight and intraday components, we use the open price generated by the collective bidding system, as reported in CSMAR. We rely on this open price to calculate the overnight, intraday, and daily open-to-open returns. The realized volatility of intraday return is calculated through the 5-minute interval return with transaction-level data from CSMAR. The daily trading volume and turnover ratio are also obtained from CSMAR. Following the Fama-French 5-factor model, we construct our control variables as follows: size, BM ratio, profitability (ROE), and investment. Institutional ownership of stocks is added to measure retail participation and short-sale constraints. PE is calculated as a proxy for market valuation. Considering the arbitrage limits, we add the realized short-sale ratio (stock lending) and the leverage buying ratio.

Our core retail sentiment measure is extracted from Xueqiu, the largest online investor community in China. It is a vertical social media platform for retail investors, founded in March 2010. Xuequ allows users to follow stocks; view real-time quotes of Shanghai, Shenzhen, Hong Kong, and U.S. stocks; exchange and discuss investment insights; create and share personal portfolios; open Shanghai, Shenzhen, and U.S. stock accounts; and buy or sell stocks and funds in real time. According to a public report from Xueqiu, the number of active user accounts was about 10 million in mid-2018, and the average daily user spent 48 minutes online each day. And the amount of current active users reaches 57 million in January 2023.[6] More importantly, since the legal risk is high for professionals (such as analysts and fund managers) to issue opinions on this platform, the majority of users are retail investors. Therefore, this creates a novel setting for isolating individual investors' emotional and rational expressions regarding stocks.

For our study, every Xueqiu post is processed using machine learning and natural language processing techniques, and a quantitative sentiment score is assigned. The accuracy of this data is also manually validated by students. Based on this score, each post is classified as positive, neutral, or negative (Mai et al. 2018). We then aggregate all posts for each stock to construct sentiment score and conformity proxies for every daytime and overnight period (Antweiler and Frank, 2004;

[6] Data source: www.xueqiu.com.

Leung and Ton, 2015; Al-Nasseri and Ali, 2018).

$$Senti\_score = \log\left(\frac{1+Post\_pos}{1+Post\_neg}\right) \tag{1}$$

$$Senti\_conform = 1-\sqrt{1-\left(\frac{Post\_pos-Post\_neg+1}{Post\_pos+Post\_neg+1}\right)^2} \tag{2}$$

Senti_score is the retail sentiment index calculated according to Equation (1), where *Post_pos* and *Post_neg* represent the number of positive and negative posts for each stock, respectively. A higher score suggests retail investors have a more positive sentiment toward a stock during that time interval. *Senti_conform* is the retail investor sentiment conformity index calculated using Equation (2). It quantifies belief dispersion among retail investors, and a higher score represents a greater convergence of retail investors' beliefs. In addition, for each stock every intraday (overnight), we collect the average number of likes, favorites, replies, and retweets, and the average number of account followers, which are proxied for the dissemination power of individual investors' opinions in the social media.

3. Summary Statistics

Table 1 provides summary statistics of our full sample based on more than 29 million posts, including more than 1.7 million firm-day observations. Panel A shows several interesting results. The average close-to-close daily return is 0.29%, but the average open-to-open daily return is 0.24%, indicating a difference greater than 20%. In addition, overnight returns are negatively significant at -0.12%, but intraday returns are positively significant at 0.40%. This negative-overnight/positive-intraday pattern contrasts with the most mature financial markets such as that in the United States. This finding is also consistent with Qiao and Dam (2020), who argue that the special "T+1" trading rule in the Chinese A-share market explains this pattern.[7] More interestingly, the daytime sentiment is 0.30, but the overnight sentiment is 0.57, which is 90% higher. This comparison is striking and suggests that individual investors generally become much more optimistic at night. In addition, there is a greater consensus of belief among individual investors overnight than during daytime, with a sentiment conformity index of 0.46 versus 0.37. Thus, a greater belief herding coincides with overly optimistic sentiment. This pattern seems to be consistent with Lou et al. (2019) and Akbas et al. (2022), who find an intense daily tug of war between opposing investor clienteles: noise traders overnight and arbitrageurs during the day.

Panel B compares from several dimensions the dissemination power of individual investors' expressions of opinion. During daytime trading hours, the average number of likes for each individual investor's tweet about each stock is 9.8, while it becomes 21.5 during overnight. A similarly striking difference is found in other interactive metrics of the online community: that is, retweets, replies, favorites, and account followers. These comparisons show that individual investors discuss more actively during the overnight period than during daytime. Our interpretation of these findings is that the overnight period persists for 18 hours, while the intraday period lasts only 6 hours. Thus, the accumulated metrics of the online community are necessarily higher during overnight.

<Table 1>

Panel C presents the sample statistics for other stock characteristics. On average, the daily short-sale ratio to total shares outstanding (*Lending*) is smaller than 0.01%, much lower than the U.S. market, implying a very strong limit to arbitrage in the China stock market. This also indicates that

[7] T+1 trading prohibits traders from selling the shares they bought on the same day. This restriction leads to a discount on daily opening prices.

it could be too costly for individual investors to borrow assets and then subsequently sell them short. By contrast, the leverage buying ratio (*Financing*) is much higher on a daily basis, standing at 0.17%. The strong asymmetry between leverage buying and short selling also implies a larger probability of upward bubbles.

<Table 2>

The average PE ratio is greater than 90%, implying a generally extreme value. The average profitability of listed firms is now 5.56% in terms of ROE, suggesting a relatively low return to shareholders. The average investment cash flow per share was -0.56%. In other words, cash outflow is greater than cash inflow and operating cash flows are used for investment purposes. Table 2 presents the Pearson and Spearman correlation matrices. Note that the correlation between sentiment and the conformity index is much stronger during overnight trading than during intraday trading (0.60 vs. 0.13). This result is consistent with the summary statistics in Panel A of Table 1.

4. Empirical Results

4.1 Validity of Our Sentiment Measure

As our sentiment measure is based on Chinese textual analyses, we begin our empirical analyses by confirming the measure's validity. First, we run a series of contemporaneous regressions to examine its correlation with other widely used sentiment proxies. Consistent with Abody et al. (2018) who use overnight returns to measure firm-specific sentiment., we also find significant co-movement between our overnight (daytime) sentiment and the overnight (daytime) return in both univariate and multivariate regressions, as shown in Panel A of Table 3. Economically, one standard-deviation increase in our firm-specific overnight sentiment coincides with a 0.21%

increase in overnight returns, which is 1.75 times the absolute value of the sample mean. These results are also consistent with those reported by Edmans et al. (2021).

<Table 3>

Panel B shows the co-movement between our sentiment measure and other sentiment proxies such as volatility, trading volume, and turnover (Baker and Wurgler 2007; Boubaker et al. 2019; Wang et al. 2022). As shown, the daytime sentiment significantly co-varies with stock turnover ratio. But the coefficient becomes insignificant in the regression of trading volume after considering other determinants, implying that trading volume may not be a good sentiment proxy. We also find significant contemporaneous correlation between daytime sentiment and intraday volatility, consistent with previous findings that investor sentiment and the resulting noise trading increase volatility (e.g., Black 1986; De Long et al. 1990; Da et al. 2015; Edmans et al. 2021). Second, we regress stock trading features based on our sentiment conformity measure. Panel C reports the results. Since conformity represents the belief dispersion among retail investors, we expect a reduced level of trading if their beliefs are less dispersed. Consistently, we find that higher sentiment conformity is associated with lower trading volumes, turnover, and volatility.

<Table 4>

Third, following Abody et al. (2018), we test the short-term persistence of our sentiment measure. Baber et al. (2009) find that the order imbalance of individual investors persists for several weeks and that these investors are most likely to trade driven by sentiment. If our sentiment measure is valid, this pattern should also be present. Empirically, we run time-series regressions for both daytime and overnight sentiments and the results are presented in Table 4. Consistently, we find that both daytime and overnight sentiments exhibit strong short-term persistence, with significantly positive autocorrelation coefficients on a daily basis. In summary, the above findings in Tables 3 and 4 lend very strong support to the validity of our new sentiment measures.

4.2 Short-term Return Predictability

In this subsection, we compare the short-term predictability of daytime and overnight sentiments. As shown in Panel A of Table 5, the daytime sentiment significantly predicts the following 1-day close-to-close daily return in both univariate and multivariate regressions. However, the overnight sentiment has no predictive power in the two regressions. One possible explanation is that the daytime window is closer to the next time interval of close-to-close daily returns, but the overnight window is farther away. Thus, the daytime sentiment could already have absorbed the predictability of the previous overnight sentiment. To test this possibility, we turn to regressions using the open-to-open daily return as the dependent variable. In this scenario, the overnight window is closer to the predicted time interval. Panel B presents the results. We still find that the daytime sentiment significantly predicts open-to-open daily returns in both regressions. However, the overnight sentiment only has marginally significant predictive power in the univariate regression. Taken together, these results imply that in the short term, daytime sentiment has stronger positive predictive power than does overnight sentiment.

<Table 5>

4.3 Information Channel versus Temporary Demand Shock

Next, we examine the mechanism behind the above differences in predictive power. Previous studies propose two opposite channels. On one hand, De Long et al. (1990) expect investor sentiment to predict market return reversal. When sentiment is high (low), irrational investors will increase (decrease) their demand for assets, driving prices up (down) and away from fundamentals.

Because of limits to arbitrage, the mispricing might not be corrected immediately (Pontiff 1996; Shleifer and Vishny 1997). However, rational investors will take advantage of mispricing, leading prices to return to their base levels over time. Empirically, Tetlock (2007) shows that news media tone is negatively predictive of stock market returns. Baker et al. (2012) construct a global and local sentiment index and find that both sentiment indices are contrarian predictors of market return. Jiang et al. (2019) textually extract a proxy for manager sentiment and find that manager sentiment negatively predicts future stock returns. Edmans et al. (2021) find that music sentiment negatively predicts next-period returns. Obaid and Pukthuanthong (2021) construct a news-photos based sentiment and find that it negatively predicts the next day's market returns. These empirical findings are consistent with the behavioral finance theory that investor sentiment is an inverse indicator.

On the other hand, some studies find that investor sentiment positively predicts future stock returns and propose the information channel hypothesis. Renault (2017) finds that the first half-hour change in investor sentiment positively predicts the last half-hour S&P 500 index ETF returns. Han and Li (2017) document that investor sentiment is a reliable momentum predictor at the monthly frequency. Gu and Kurov (2020) find that Twitter sentiment predicts stock returns without subsequent reversals and provides new information about analysts' recommendations, price targets, and quarterly earnings. In the credit market, Laborda and Olmo (2014) and Çepni et al. (2020) also document that investor sentiment positively predicts expected excess bond returns. Cortés et al. (2016) find that positive investor sentiment is associated with higher credit approvals. These studies are consistent with the notion that investor sentiment contains valuable fundamental information.

To differentiate the above two opposite channels, we examine whether the equity price reverses after the first day's response to the retail sentiment. If individual investors create mispricing with their irrational sentiment, pushing the asset price above or below its fundamental price, the asset price should return to a rational level after a short-term deviation. Empirically, we use lagged 1-day sentiment to predict longer-term returns: that is, returns in the 2-day, 3-day, 1-week, 1-month, 3-month, and 6-month windows.

<Table 6>

As shown in Panel A of Table 6, we find that the positive short-term predictability of the overnight sentiment starts to reverse on the second day, as indicated by the insignificant coefficient in the regression of the 2-day window. More interestingly, from the 1-week to 6-month period afterward, the overnight sentiment even starts to become a significantly negative indicator of future returns. This reversal pattern implies that the temporary overnight demand shock from individual investors creates 1-day overpricing that is corrected in the longer term. This is also consistent with the behavioral hypothesis that investor sentiment is an irrational inverse indicator (e.g., Tetlock 2007; Baker et al. 2012; Jiang et al. 2019; Edmans et al. 2021).

On the contrary, the daytime sentiment can consistently and positively predict the following return up to a 6-month window without any reversal, as shown in Panel B. This suggests that the sentiment in the daytime trading session could contain valuable fundamental information about the underlying assets, which supports its consistent long-term predictability. In this scenario, we should observe that daytime sentiment can predict firms' fundamental information. Empirically, we test whether daytime sentiment can predict firms' earnings surprises.

<Table 7>

Specifically, we use the average daytime (overnight) sentiment over the 1-month, 3-month, and 6-month periods before the quarterly earnings announcement as the predictor, and then regress the earnings surprise on it. As shown in Table 7, the average intraday sentiment of the 3-month and 6-month can significantly and positively predict the following earnings surprise, but this pattern is not found for overnight sentiment. These results confirm that the overall daytime sentiment contains fundamental information, but that the overall overnight sentiment is overwhelmed by noise.

Taken together, these findings are consistent with the clientele heterogeneity in different trading sessions. During the daytime, individual investors are performing their day jobs instead of posting in the investor community; however, the professional or more informed arbitrageurs are focusing on stock investing while exchanging their opinions on the platform, thus dominating the daytime sentiment. In addition, their beliefs are simultaneously adjusted by real-time trading, which contains valuable information. Thus, daytime sentiment should be more rational and contain fundamental information. In contrast, during the overnight period, most individual investors become active on social media and dominate sentiment with their variable moods.

4.4 The Role of Social Media Dissemination Power

Very few studies have examined retail investors' sentiment from the perspective of social media dissemination power, which is a quite distinct feature of online community. We try to fill this gap using the rich metrics of our data. Social media is a real-time and instant communication platform for information dissemination and acquisition. Different accounts or posts have very different influences in a platform, which could affect both capital market and political agenda such as Presidential Elections. Specifically, we define the dissemination power of a social media post from following dimensions: the number of likes, the number of retweets, the number of favorites, the number of replies, and the number of account followers. We conjecture that when a post provides more insightful interpretations of public information or directly provides private information, it will attract more attention and will be distributed more widely. If an account already is a key opinion leader, given that it has accumulated followers and influence before, the account's future posts can also be disseminated more quickly.

<Table 8>

<Table 9>

First, we explore the effect of dissemination power on the short-term return predictability of sentiments. As presented in Table 8, the short-term positive predictability of both daytime and overnight sentiment is much more significant when retail investors' posts have stronger dissemination power. Interestingly, if overnight posts have weaker dissemination with fewer retweets, favorites or replies, the sentiment negatively predicts the following daily open-to-open returns, suggesting that those relatively low-quality overnight post is a negative indicator even in the short term. Table 9 presents similar analyses for long-term predictability. Consistently, the daytime sentiment from high-quality posts has more pronounced positive long-term predictability without reversal, but the overnight sentiment from low-quality posts is a clearer inverse indicator.

<Table 10>

Also, we examine the mediating role of dissemination power in the relationship between retail sentiment and contemporaneous stock return. As shown in Table 10, the simultaneous covariation between the sentiment and return is stronger when retail posts have greater dissemination power for both trading sessions. Taken together, the above findings in this section imply that the post-specific dissemination feature is a key factor in analyzing social media sentiment for the future research.

5. Additional Analysis

In this section, we analyze whether the sentiment's short-term return predictability can be used in practical investment. For each trading day, we first sort all stocks into five quintiles based on seven sentiment-based measures: the level of daytime sentiment, the level of overnight sentiment, the level of full day sentiment, the daily change in daytime sentiment, the daily change in overnight sentiment, the daily change in full day sentiment, and the difference between daytime and overnight sentiment (the "tug of war" measure). Then we construct hedging portfolios by buying stocks in the 1st quintile and short-selling stocks in the 5th quintile. The portfolios are rebalanced every trading day and two types of portfolios are built: open-to-open trade and close-to-close trade. Figure 1 shows the cumulative returns for each strategy from 2016/01/01 to 2020/12/31. The trend of the CSI300 index is plotted as a benchmark.

<Figure 1>

Table 11 shows the annualized returns and Sharp ratio for each trading strategy, after considering the round-trip commission costs range from 0 to 0.03%.[8] Several findings are noteworthy. First, consistent with the regressions, the trading strategy based on the daytime sentiment generates positive annualized return, whereas the trading strategy based on the overnight sentiment produces a negative return (e.g., 35.3% vs. -12%, with round-trip commission costs of 0.02%). Second, the close-to-close trading strategies are superior to the open-to-open trading strategies for most

[8] We conservatively hypothesize that all the stocks in each portfolio will be rebalanced every day.

sentiment measures. This comparison suggests that buying at market open is not a good trading decision when individual investors are crowding.

<Table 9>

Third, a strategy based on the level of daily sentiment produces much a better return than a strategy based on the change of daily sentiment (e.g., 43.6% vs. 20.3%, with round-trip commission costs of 0.02%). As we know, the literature mainly uses the change of daily sentiment to predict future returns and to build hedging portfolios (Lee et al. 1991; Han 2008; Kurov 2010). Our finding implies that the level of retail sentiment seems to be a more sensitive indicator of potential future return. Lastly, we find that the tug of war measure of individual sentiment (the difference between daytime and overnight sentiment) performs quite well and generate an annualized return of 25.7% accounting for the commissions costs of 0.02%. And when the trading commission is relatively low, it even generates the highest Sharpe ratio and shows the best risk-return trade-off.

6. Conclusion

Investor behaviors on social media change over time, which suggests that the status and influence of investor sentiment on the stock market can be different. In this study, we provide a novel decomposition of the popular firm-specific sentiment measures into daytime and overnight sentiment. We first briefly compare the two sentiments and find striking differences. The overall optimism in investor social media is much higher during the night than during the daytime, and the individual belief convergence is also much stronger. These patterns are consistent with the individual herding during the night. We then show that the daytime sentiment has much stronger predictive power for the future short-term daily returns, including the close-to-close and open-to-open returns. But the predictive power of overnight sentiment is much weaker, both in statistical and economical significance. This difference again pushes us to examine the behind mechanism.

We document that the daytime sentiment can positively predict future returns for up to 6 months, while the predictability of overnight sentiment shows a long-run reversal pattern.
Also, we examine the sentiment's predictability in terms of firm's fundamental information. We find that the daytime sentiment has significant predictability for the future earnings surprises, whereas the overnight sentiment is not associated with future earnings. Taken all together, our findings provide further support to the clientele heterogeneity hypothesis that the large amount of individual investors dominate the overnight trading and sentiment, while the smaller number of more professional arbitrageurs still focus on trading during the daytime and mainly constitute the daytime sentiment.

We also first study the effect of social media dissemination power on the sentiment. Quite few studies focus on this distinct feature of social media, and we define the dissemination power based on the rich metrics of our textual data. We find that the daytime sentiment has much more pronounced predictability for both short-term and long-term return if it's extracted from the widely disseminated high-quality posts. And the overnight sentiment is a stronger contrarian indicator of future return if it's constructed based on low-quality posts.

Though our findings are based on the high frequency breakdown of daily sentiment, they also have important implication for the practitioners. We construct the trading strategies based on the daytime and overnight sentiment. After accounting for a reasonable round-trip commission cost of 0.02%, our daily rebalanced trading strategy based on daytime sentiment produces a large annualized return of 35.3%. The risk-return trade-off is also very attractive, given the Sharpe ratio is as high as 3.06. Generally, our finding that daytime sentiment level can guide large scale stock selection should be of wide interest to fund managers. We also hope our decomposition offers a step for future academic research to examine other systemic differences between daytime and overnight sentiments.

References

Al-Nasseri, A., Menla Ali, F., & Tucker, A. (2017). Dispersion of stock returns and investor sentiment: StockTwits evidence. Unpublished Paper.

Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets*, 5(1), 31-56.

Antweiler, W., & Frank, M. Z. (2004). Is all that talk just noise? The information content of Internet stock message boards. *The Journal of Finance*, 59(3), 1259-1294.

Baker, M., & Stein, J. C. (2004). Market liquidity as a sentiment indicator. *Journal of Financial Markets*, 7(3), 271-299.

Bamber, L. S., Barron, O. E., & Stober, T. L. (1997). Trading volume and different aspects of disagreement coincident with earnings announcements. *The Accounting Review*, 72(4), 575-597.

Banerjee, S. (2011). Learning from prices and the dispersion in beliefs. *The Review of Financial Studies*, 24(9), 3025-3068.

Banerjee, S., & Kremer, I. (2010). Disagreement and learning: Dynamic patterns of trade. *The Journal of Finance*, 65(4), 1269–1302.

Berkman, H., Dimitrov, V., Jain, P. C., Koch, P. D., & Tice, S. (2009). Sell on the news: Differences of opinion, short-sales constraints, and returns around earnings announcements. *Journal of Financial Economics*, 92(3), 376-399.

Bokányi, E., Lábszki, Z., & Vattay, G. (2017). Prediction of employment and unemployment rates from Twitter daily rhythms in the US. EPJ Data Science, 6(14), Available at: https://doi.org/10.1140/epjds/s13688-017-0112-x

Bollen, J., Mao, H., & Zeng, X-J. (2011). Twitter mood predicts the stock market. *Journal Computational Science*, 2(1), 1–8.

Bukovina, J. (2016). Social media big data and capital markets-An overview. *Journal of Behavioral and Experimental Finance*, 11, 18–26.

Carlin, B. I., Longstaff, F. A., & Matoba, K. (2014). Disagreement and asset prices. *Journal of Financial Economics*, 114(2), 226–238.

Chen, J., Hong, H., & Stein, J. C. (2002). Breadth of ownership and stock returns. *Journal of Financial Economics*, 66(2-3), 171-205.

Chen, L., Qin, L., & Zhu, H. (2015). Opinion divergence, unexpected trading volume and stock returns: Evidence from China. *International Review of Economics and Finance*, 36, 119-127.

Choi, H., & Varian, H. (2012). Predicting the present with Google trends. *Economic Record*, 88(s1), 2–9.

Chordia, T., Roll, R., & Subrahmanyam, A. (2001). Market liquidity and trading activity. *The Journal of Finance*, 56(2), 501-530.

Chung, S-L., Hung, C-H., & Yeh, C-Y. (2012). When does investor sentiment predict stock returns?. *Journal of Empirical Finance*, 19(2), 217–240.

D'Amuri, F., & Marcucci, J. (2017). The predictive power of Google searches in forecasting US unemployment. *International Journal of Forecasting*, 33(4), 801-816.

D'Avolio, G. (2002). The market for borrowing stock. *Journal of Financial Economics*, 66(2-3), 271–306.

David, A. (2008). Heterogeneous beliefs, speculation, and the equity premium. *The Journal of Finance*, 63(1), 41–83.

De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Noise trader risk in financial markets. *Journal of Political Economy*, 98(4), 703-738.

Diether, K. B., Malloy, C. J., & Scherbina, A. (2002). Differences of opinion and the cross section of stock returns. *The Journal of Finance*, 57(5), 2113-2141.

Fang, L. H., & Peress, J. (2009). Media coverage and the cross-section of stock returns. *The Journal of Finance*, 64(5), 2023-2052.

Garfinkel, J. A., & Sokobin, J. (2006). Volume, opinion divergence and returns: A study of post-earnings announcement drift. *Journal of Accounting Research*, 44(1), 85-112.

Giannini, R. C., Irvine, P. J., & Shu, T. (2015). The convergence and divergence of investors' opinions around earnings news: Evidence from a social network.

Harris, M., & Raviv, A. (1993). Differences of opinion make a horse race. *The Review of Financial Studies*, 6(3), 473-506.

Hong, H., & Stein, J. C. (2003). Differences of opinion, short-sales constraints, and market crashes. *The Review of Financial Studies*, 16(2), 487–525.

Jegadeesh, N., & Titman, S. (2001). Profitability of momentum strategies: An evaluation of alternative explanations. *The Journal of Finance*, 56(2), 699-720.

Johnson, T. C. (2004). Forecast dispersion and the cross section of expected returns. *The Journal of Finance*, 59(5), 1957-1978.

Kandel, E., & Pearson, N. D. (1995). Differential interpretation of public signals and trade in speculative markets. *Journal of Political Economy*, 103(4), 831-872.

Lakonishok, J., & Maberly, E. (1990). The weekend effect: Trading patterns of individual and institutional investors. *The Journal of Finance*, 45(1), 231-243.

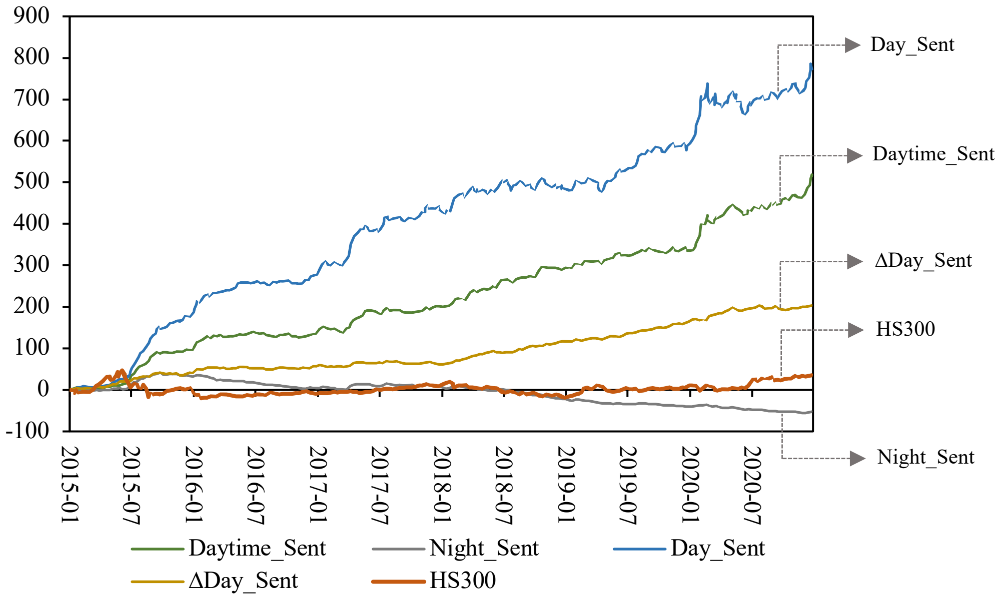
Appendix: Definitions of Variables

Variable	Definition
Ret_Close	Close-to-close daily stock return (%), measure as the difference between closing price and closing price of the last trading day, divided by closing price. Data are from CSMAR.
Ret_Open	Open-to-open daily stock return (%), measure as the difference between opening price and opening price of the last trading day, divided by closing price. Data are from CSMAR.
Ret_night	Overnight stock return (%), measure as the difference between opening price and closing price of the last trading day, divided by closing price of the last trading day. Data are from CSMAR.
Ret_daytime	Overnight stock return (%), measure as the difference between closing price and opening price, divided by opening price. Data are from CSMAR.
Night_Sent	Retail investors' overnight sentiment during non-trading hours (from 15:00 to 9:00 the next day), measure as the natural logarithm of number of bullish posts plus one divided by number of bearish posts plus one.
Daytime_Sent	Retail investors' intraday sentiment during trading hours (from 9:00 to 15:00), measure as the natural logarithm of number of bullish posts plus one divided by number of bearish posts plus one.
Day_Sent	Retail investors' daily sentiment, measure as the average of retail investors' overnight sentiment and intraday sentiment.
Night_Like	The total number of users' likes on all posts during non-trading hours.
Night_Favor	The total number of users' adds to favorites for all posts during non-trading hours.
Night_Retweet	The total number of users' retweets of all posts during non-trading hours.
Night_Reply	The total number of users' replies to all posts during non-trading hours.
Night_Follower	The average number of followers of the post users during non-trading hours.
Night_Conform	User sentiment consistency index during non-trading hours.
Daytime_Like	The total number of users' likes on all posts during trading hours.
Daytime_Favor	The total number of users' adds to favorites for all posts during trading hours.
Daytime_Retweet	The total number of users' retweets of all posts during trading hours.
Daytime_Reply	The total number of users' replies to all posts during trading hours.
Daytime_Follower	The average number of followers of the post users during trading hours.
Daytime_Conform	User sentiment consistency index during trading hours.
Volatility	The intraday stock realized volatility, calculated by 5-minute interval return with transaction level data from CSMAR.
Volume	The natural logarithm of intraday stock trading volume. Data are from CSMAR.
Turnover	The intraday stock turnover, measure as the intraday stock trading amount divided by circulation market value. Data are from CSMAR.
Size	The natural logarithm of stock circulation market value. Data are from CSMAR.
BM	Book-to-market ratio, measured as the total assets divided by the market value. Data are from CSMAR.
PE	PE ratio, measure as the market value divided by the sum of net profit for the last four quarters. Data are from CSMAR.
Financing	Leverage buying ratio, measure as the intraday total amount of the underlying securities purchased by credit traders through financing business divided by stock circulation market value. Data are from CSMAR.
Lending	Short-sale ratio, measure as the total volume of the underlying securities sold by credit traders through lending business divided by circulation stock. Data are from CSMAR.
ROE	Return on equity, measure as net income divided by balance of shareholders' equity. Data are

	from CSMAR.
Leverage	Debt-to-asset ratio, measure as the total debts divided by the total assets. Data are from CSMAR.
Investment	Investment cash flow per share, measure as current value of net cash flow generated from investing activities divided by current value of paid-in capital. Data are from CSMAR.
InstOwnership	The ratio of Institutional ownership, measure as shared held institutional investors divided by total shares outstanding. Data from CSMAR.
ES	Earnings surprise, measure as the real EPS minus the average EPS predicted by institutions or analysts for the 1, 3, and 6 months prior to the expiration date.

Figure 1. Cumulative Returns for Sentiment-based Portfolios.
This figure shows the cumulative returns for the portfolios constructed based on level of intraday sentiment, the level of overnight sentiment, the level of daily sentiment, the daily change in intraday sentiment, the daily change in overnight sentiment, the daily change in daily sentiment, and the difference between intraday and overnight sentiment. All the portfolios are daily rebalanced by buying the stocks with its sentiment measure in the 1st quintile and selling the stocks with its sentiment measure in the 5th quintile. The full sample is based on all the A-share stocks and the investment period is from 2016/01/01-2020/12/31. Panel A presents the portfolios based on the close-to-close return, and Panel B presents the portfolios based on the open-to-open return.

Panel A: Market close-to-close strategy



Panel B: Market open-to-open strategy

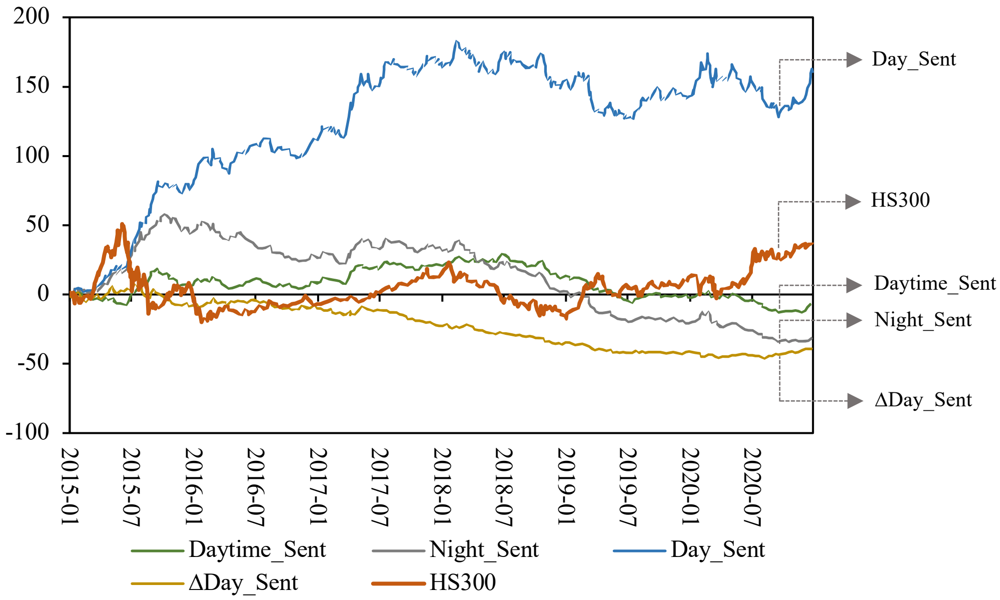


Table 1: Summary Statistics

This table presents the summary statistics for the variables used in our analysis. Minimum, median (P50), and Maximum are displayed. The sample period is from 2016/01/01-2020/12/31. Variable definitions are provided in the Appendix.

Panel A

Variable	Obs	Mean	Std. Dev.	Min	Median	Max
Ret_Close	1,749,048	0.29	3.67	-9.98	0.14	10
Ret_Open	1,749,048	0.24	3.58	-10.30	0.09	10.79
Ret_night	1,749,048	-0.12	1.48	-5.38	0	5.56
Ret_daytime	1,749,048	0.40	3.24	-7.99	0.19	9.48
Daytime_Sent	1,749,048	0.30	0.80	-1.50	0.41	2.08
Night_Sent	1,749,048	0.58	0.83	-1.39	0.69	2.60

Panel B

(a) Daytime Variable

Variable	Obs	Mean	Std. Dev.	Min	Median	Max
Daytime_Like	1,749,048	9.87	25.57	0	1	174
Daytime_Favor	1,749,048	6.55	22.57	0	0	170
Daytime_Retweet	1,749,048	2.37	7.63	0	0	56
Daytime_Reply	1,749,048	10.48	25.59	0	2	173
Daytime_Follower	1,749,048	15286.63	69112.98	0	1905	631355
Daytime_Conform	1,749,048	0.37	0.44	0	0.13	1

(b) Night Variable

Variable	Obs	Mean	Std. Dev.	Min	Median	Max
Night_Like	1,749,048	21.60	56.92	0	2	386
Night_Favor	1,749,048	22.90	68.80	0	1	489
Night_Retweet	1,749,048	6.56	18.98	0	0	134
Night_Reply	1,749,048	19.76	49.28	0	3	334
Night_Follower	1,749,048	30274.33	160490.20	0	3564	1401971
Night_Conform	1,749,048	0.47	0.44	0	0.2419	1

Panel C

Variable	Obs	Mean	Std. Dev.	Min	Median	Max
Volatility	1,749,048	11.92	14.59	0.50	6.41	76.22
Volume	1,749,048	16.24	1.22	12.76	16.25	18.80
Turnover	1,749,048	3.95	4.91	0.10	2.11	23.49
Size	1,749,048	15.98	1.20	13.37	15.88	18.90
BM	1,749,048	0.59	0.27	0.10	0.57	1.17
PE	1,749,048	93.50	158.85	6.50	44.64	1080.26
Financing	1,749,048	0.17	0.32	0	0	1.39
Lending	1,749,048	0.003	0.007	0	0	0.04
ROE	1,749,048	5.56	7.22	-43.04	4.63	25.46
Leverage	1,749,048	43.59	21.61	5.47	42.28	94.52
Investment	1,749,048	-0.56	1.07	-5.43	-0.23	1.34

Table 2: Correlation Matrix

This Table reports the correlation matrix between variables. Lower-triangular cells report Pearson's correlation coefficients, upper-triangular cells report Spearman's rank correlation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1) Ret_Close	1	0.15***	0.33***	0.89***	0.19***	0.23***	0.08***	0.11***	-0.02***	-0.04***	0.05***	-0.01***	0.00**	-0.02***	-0.02***	0.01***	-0.02***
(2) Ret_Open	0.22***	1	0.36***	-0.01***	0.13***	0.09***	0.06***	0.04***	-0.01***	-0.03***	0.04***	0.01***	-0.02***	-0.02***	-0.01***	0.01***	-0.02***
(3) Ret_night	0.39***	0.51***	1	-0.02***	0.11***	0.10***	0.05***	0.05***	0.05***	0.00***	-0.04***	0.04***	0.04***	0.03***	0.01***	-0.01***	0.04***
(4) Ret_daytime	0.89***	-0.02***	-0.05***	1	0.15***	0.21***	0.06***	0.10***	-0.04***	-0.04***	0.06***	-0.02***	-0.01***	-0.03***	-0.02***	0.02***	-0.04***
(5) Daytime_Sent	0.19***	0.14***	0.12***	0.15***	1	0.24***	0.77***	0.17***	0.01***	-0.03***	0.02***	-0.00***	0.01***	0.00*	-0.01***	-0.00	0.04***
(6) Night_Sent	0.27***	0.10***	0.12***	0.23***	0.25***	1	0.12***	0.73***	0.07***	-0.05***	0.01***	0.04***	0.05***	0.04***	-0.01***	-0.02***	0.07***
(7) Daytime_Conform	0.04***	0.03***	0.03***	0.03***	0.66***	0.08***	1	0.20***	-0.11***	0.00***	0.01***	-0.11***	-0.10***	-0.04***	-0.04***	0.02***	-0.03***
(8) Night_Conform	0.07***	0.02***	0.04***	0.06***	0.13***	0.60***	0.25***	1	-0.14***	0.00***	0.02***	-0.13***	-0.12***	-0.03***	-0.05***	0.02***	-0.05***
(9) Size	-0.02***	-0.02***	0.04***	-0.04***	0.03***	0.07***	-0.18***	-0.20***	1	0.08***	-0.28***	0.70***	0.63***	0.20***	0.34***	-0.06***	0.52***
(10) BM	-0.04***	-0.03***	0.00***	-0.04***	-0.03***	-0.05***	0.02***	0.02***	0.12***	1	-0.51***	0.11***	0.17***	-0.10***	0.53***	-0.09***	0.09***
(11) PE	0.05***	0.04***	-0.02***	0.06***	0.01***	-0.00	0.01***	0.01***	-0.27***	-0.50***	1	-0.19***	-0.22***	-0.30***	-0.22***	0.09***	-0.27***
(12) Financing	-0.03***	-0.02***	0.03***	-0.04***	0.01***	0.04***	-0.12***	-0.14***	0.67***	0.17***	-0.23***	1	0.76***	0.06***	0.24***	-0.03***	0.33***
(13) Lending	-0.01***	-0.02***	0.03***	-0.02***	0.02***	0.06***	-0.14***	-0.16***	0.63***	0.17***	-0.21***	0.76***	1	0.07***	0.23***	-0.04***	0.33***
(14) ROE	-0.01***	-0.01***	0.02***	-0.03***	0.01***	0.05***	-0.05***	-0.04***	0.19***	-0.11***	-0.24***	0.07***	0.07***	1	-0.03***	-0.27***	0.24***
(15) Leverage	-0.02***	-0.01***	0.01***	-0.02***	-0.01***	-0.01***	-0.05***	-0.06***	0.36***	0.54***	-0.22***	0.24***	0.24***	-0.07***	1	-0.10***	0.18***
(16) Investment	0.01***	0.01***	-0.00***	0.02***	0.00	-0.01***	0.04***	0.04***	-0.07***	-0.10***	0.10***	-0.03***	-0.05***	-0.20***	-0.11***	1	-0.13***
(17) InstOwnership	-0.02***	-0.02***	0.02***	-0.03***	0.04***	0.07***	-0.05***	-0.07***	0.51***	0.15***	-0.27***	0.34***	0.33***	0.19***	0.21***	-0.10***	1

Table 3: Contemporaneous relation between investor sentiment and stock trading

This table shows the contemporaneous relation between investor sentiment measures textually extracted from Xueqiu and stock trading activities. Panel A shows the contemporaneous relationship between sentiment and stock return for intraday and overnight. Panel B shows the contemporaneous relationship between daytime sentiment and stock return volatility, trading volume and turnover ratio. Panel C shows the contemporaneous relationship between daytime sentiment conformity measure and stock trading activities. All variables are defined in the Appendix. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A

	Ret_night		Ret_daytime	
	(1)	(2)	(3)	(4)
Night_Sent	0.2523***	0.2533***		
	(0.0048)	(0.0048)		
Daytime_Sent			0.5544***	0.5491***
			(0.0080)	(0.0080)
Size		-0.0216**		0.0303
		(0.0089)		(0.0234)
BM		0.0433		-0.1982***
		(0.0278)		(0.0698)
PE		-0.0218***		0.1368***
		(0.0037)		(0.0093)
Financing		-0.0002		-0.0163***
		(0.0005)		(0.0012)
Lending		0.0028***		0.0466***
		(0.0007)		(0.0018)
ROE		0.0027***		-0.0036***
		(0.0004)		(0.0009)
Leverage		0.0011***		-0.0015**
		(0.0003)		(0.0006)
Investment		0.0040**		0.0064
		(0.0017)		(0.0044)
InstOwnership		0.0004***		-0.0008***
		(0.0001)		(0.0002)
Constant	-0.2870***	0.0373	0.2369***	-0.5898
	(0.0032)	(0.1550)	(0.0023)	(0.4064)
N	1573800	1573800	1749039	1749039
$Adj.R^2$	0.288	0.288	0.313	0.315
Date FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Panel B

	Volatility		Volume		Turnover	
	(1)	(2)	(3)	(4)	(5)	(6)
Daytime_Sent	0.7638***	0.6924***	0.0109***	0.0025	0.0334***	0.0328***
	(0.0325)	(0.0323)	(0.0024)	(0.0023)	(0.0097)	(0.0091)
Size		0.3618**		0.3307***		-1.6383***
		(0.1477)		(0.0190)		(0.0764)
BM		-5.7712***		-0.0091		-2.2478***
		(0.4741)		(0.0594)		(0.2354)
PE		2.3611***		0.1004***		0.8345***
		(0.0831)		(0.0082)		(0.0372)
Financing		-0.0673***		0.0116***		0.0279***
		(0.0099)		(0.0015)		(0.0054)
Lending		0.1609***		0.0286***		0.0984***
		(0.0101)		(0.0011)		(0.0043)
ROE		-0.0506***		-0.0047***		0.0094***
		(0.0066)		(0.0009)		(0.0033)
Leverage		-0.0147***		0.0023***		-0.0312***
		(0.0056)		(0.0007)		(0.0030)
Investment		-0.0182		0.0261***		-0.2107***
		(0.0369)		(0.0052)		(0.0237)
InstOwnership		-0.0100***		-0.0029***		-0.0122***
		(0.0014)		(0.0002)		(0.0007)
Constant	11.6862***	1.2517	16.2382***	10.3693***	3.9437***	29.0484***
	(0.0091)	(2.5424)	(0.0007)	(0.3194)	(0.0026)	(1.2871)
N	1749039	1749039	1749039	1749039	1749039	1749039
Adj.R^2	0.422	0.437	0.659	0.688	0.470	0.496
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel C

	Volatility		Volume		Turnover	
	(1)	(2)	(3)	(4)	(5)	(6)
Daytime_Conform	-4.0826***	-3.8082***	-0.4111***	-0.3673***	-1.7507***	-1.7535***
	(0.0626)	(0.0578)	(0.0044)	(0.0040)	(0.0281)	(0.0270)
Size		0.1351		0.3066***		-1.7527***
		(0.1434)		(0.0184)		(0.0740)
BM		-5.4514***		0.0273		-2.0755***
		(0.4637)		(0.0576)		(0.2256)
PE		2.3063***		0.0935***		0.8020***
		(0.0811)		(0.0080)		(0.0355)
Financing		-0.0671***		0.0116***		0.0278***
		(0.0097)		(0.0014)		(0.0051)
Lending		0.1440***		0.0268***		0.0898***
		(0.0099)		(0.0011)		(0.0041)
ROE		-0.0499***		-0.0047***		0.0095***
		(0.0064)		(0.0008)		(0.0031)
Leverage		-0.0143***		0.0023***		-0.0310***
		(0.0054)		(0.0007)		(0.0029)
Investment		-0.0003		0.0277***		-0.2031***
		(0.0357)		(0.0050)		(0.0227)
InstOwnership		-0.0077***		-0.0027***		-0.0113***
		(0.0013)		(0.0002)		(0.0007)
Constant	13.4348***	6.5236***	16.3944***	10.8991***	4.6047***	31.5705***
	(0.0212)	(2.4677)	(0.0015)	(0.3095)	(0.0100)	(1.2470)
N	1749039	1749039	1749039	1749039	1749039	1749039
Adj.R^2	0.434	0.447	0.678	0.703	0.491	0.518
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 4: Short-term persistence of sentiment measures
This table tests the short-term persistence of investor sentiment measures textually extracted from Xueqiu. Both univariate and multivariate regressions are presented. All variables are defined in the Appendix. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	F.Night_Sent		F.Daytime_Sent	
	(1)	(2)	(3)	(4)
Night_Sent	0.1690***	0.1626***		
	(0.0019)	(0.0018)		
Daytime_Sent			0.1615***	0.1595***
			(0.0018)	(0.0017)
Size		0.0542***		0.0349***
		(0.0066)		(0.0066)
BM		-0.2125***		-0.0862***
		(0.0218)		(0.0212)
PE		0.0311***		0.0221***
		(0.0031)		(0.0031)
Financing		-0.0002		0.0004
		(0.0005)		(0.0005)
Lending		0.0043***		0.0025***
		(0.0004)		(0.0004)
ROE		0.0023***		0.0006**
		(0.0003)		(0.0003)
Leverage		-0.0001		-0.0001
		(0.0003)		(0.0002)
Investment		-0.0024		0.0013
		(0.0018)		(0.0019)
InstOwnership		0.0006***		0.0005***
		(0.0001)		(0.0001)
Constant	0.4746***	-0.4266***	0.2434***	-0.3769***
	(0.0012)	(0.1137)	(0.0004)	(0.1131)
N	1573800	1573800	1484281	1484281
$Adj.R^2$	0.165	0.169	0.118	0.120
Date FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Table 5: Short-term Return Predictability of daytime and overnight sentiment

This table shows the short-term return predictability of daytime and overnight sentiment measures textually extracted from Xueqiu. Panel A shows the predictability for the close-to-close daily return. Panel B shows the predictability for the open-to-open daily return. All variables are defined in the Appendix. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A

	Ret_Close			
	1-day	1-day	1-day	1-day
	(1)	(2)	(3)	(4)
Daytime_Sent	0.1143***	0.0644***		
	(0.0067)	(0.0055)		
Night_Sent			0.0079	-0.0012
			(0.0075)	(0.0068)
Size		-1.0263***		-1.0365***
		(0.0353)		(0.0350)
BM		-3.2809***		-3.2759***
		(0.1094)		(0.1071)
PE		-0.1589***		-0.1537***
		(0.0122)		(0.0121)
Financing		0.0096***		0.0094***
		(0.0014)		(0.0014)
Lending		-0.0063***		-0.0058***
		(0.0019)		(0.0019)
ROE		0.0054***		0.0052***
		(0.0013)		(0.0013)
Leverage		0.0073***		0.0072***
		(0.0009)		(0.0009)
Investment		-0.0149***		-0.0142**
		(0.0057)		(0.0057)
InstOwnership		0.0008***		0.0008***
		(0.0002)		(0.0002)
Ret_close		0.0677***		0.0680***
		(0.0050)		(0.0051)
Constant	0.1924***	18.7780***	0.2422***	18.9466***
	(0.0017)	(0.6183)	(0.0046)	(0.6107)
N	1484281	1484021	1555286	1554929
Adj.R^2	0.303	0.313	0.304	0.314
Date FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Panel B

	Ret_Open			
	1-day	1-day	1-day	1-day
	(1)	(2)	(3)	(4)
Daytime_Sent	0.0424***	0.0569***		
	(0.0064)	(0.0057)		
Night_Sent			0.0125*	0.0294***
			(0.0076)	(0.0065)
Size		-0.9491***		-0.9622***
		(0.0333)		(0.0327)
BM		-3.0861***		-3.0700***
		(0.1046)		(0.1020)
PE		-0.1403***		-0.1372***
		(0.0115)		(0.0112)
Financing		0.0093***		0.0092***
		(0.0014)		(0.0014)
Lending		0.0001		-0.0005
		(0.0018)		(0.0018)
ROE		0.0048***		0.0052***
		(0.0012)		(0.0012)
Leverage		0.0073***		0.0070***
		(0.0009)		(0.0009)
Investment		-0.0178***		-0.0144***
		(0.0054)		(0.0053)
InstOwnership		0.0009***		0.0009***
		(0.0002)		(0.0002)
Ret_open		-0.0181***		-0.0118***
		(0.0044)		(0.0045)
Constant	0.1658***	17.3272***	0.1989***	17.5153***
	(0.0018)	(0.5843)	(0.0047)	(0.5718)
N	1379677	1378500	1555286	1553555
Adj.R^2	0.305	0.312	0.308	0.314
Date FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Table 6: Long-term Return Predictability of intraday and overnight sentiment

This table shows the long-term return predictability of intraday and overnight sentiment measures textually extracted from Xueqiu. Panel A shows the predictability of intraday sentiment for the future close-to-close return. Panel B shows the predictability of overnight sentiment for the future open-to-open return. The 2-day, 3-day, 1-week, 1-month, 3-month, and 6-month returns are regressed on the lagged one-day sentiments. All variables are defined in the Appendix. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A

	Ret_Open					
Term	2-day	3-day	1-week	1-month	3-month	6-month
	(1)	(2)	(3)	(4)	(5)	(6)
Night_Sent	0.0092	-0.0107	-0.0337**	-0.1908***	-0.3063***	-0.3323***
	(0.0095)	(0.0114)	(0.0141)	(0.0295)	(0.0501)	(0.0698)
N	1553555	1553555	1553555	1553548	1553257	1544224
Adj.R^2	0.326	0.334	0.357	0.434	0.435	0.385
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Panel B

	Ret_Close					
Term	2-day	3-day	1-week	1-month	3-month	6-month
	(1)	(2)	(3)	(4)	(5)	(6)
Daytime_Sent	0.0795***	0.0806***	0.0897***	0.1038***	0.0992**	0.2249***
	(0.0077)	(0.0093)	(0.0123)	(0.0269)	(0.0492)	(0.0692)
N	1484021	1484021	1484021	1484015	1483739	1474859
Adj.R^2	0.321	0.330	0.351	0.430	0.433	0.387
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: Investor Sentiment and Earnings Surprise

This table shows the earnings surprise predictability of daytime and overnight sentiment measures textually extracted from Xueqiu. Panel A shows the predictability of daytime and overnight sentiment for the earnings announcement in 1 month, Panel B shows the predictability of the idaytime and overnight sentiment for the earnings announcement in 3 months, and Panel C shows the predictability of the daytime and overnight sentiment for the earnings announcement in 6 months. All variables are defined in the Appendix. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A

	ES			
	(1)	(2)	(3)	(4)
Average 1-month				
Daytime_Sent	0.0031	0.0076		
	(0.0109)	(0.0100)		
Night_Sent			0.0156	0.0082
			(0.0103)	(0.0097)
N	3090	3090	3090	3090
$Adj.R^2$	0.065	0.242	0.066	0.242
Date FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes

Panel B

	ES			
	(1)	(2)	(3)	(4)
Average 3-month				
Daytime_Sent	0.0223***	0.0182**		
	(0.0085)	(0.0085)		
Night_Sent			0.0199**	0.0074
			(0.0089)	(0.0088)
N	8274	8274	8274	8274
$Adj.R^2$	0.056	0.090	0.056	0.089
Date FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes

Panel C

	ES			
	(1)	(2)	(3)	(4)
Average 6-month				
Daytime_Sent	0.0263**	0.0232**		
	(0.0112)	(0.0112)		
Night_Sent			0.0154	0.0049
			(0.0110)	(0.0117)
N	10118	10118	10118	10118
$Adj.R^2$	0.091	0.118	0.090	0.117
Date FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes

Table 8: The effect of dissemination power on the investor sentiment's short return predictability

This table shows the effect of dissemination power on the short-term return predictability of intraday and overnight sentiment measures textually extracted from Xueqiu. Panel A shows the predictability for the close-to-close daily return. Panel B shows the predictability for the open-to-open daily return. All variables are defined in the Appendix. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A

	Ret_Close 1-day									
	Daytime_Like		Daytime_Favor		Daytime_Retweet		Daytime_Reply		Daytime_Follower	
	High	Low	High	Low	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Daytime_Sent	0.1079***	0.0340***	0.0748***	0.0306***	0.0899***	0.0329***	0.1375***	0.0142***	0.0664***	0.0561***
	(0.0091)	(0.0059)	(0.0083)	(0.0050)	(0.0086)	(0.0051)	(0.0085)	(0.0050)	(0.0074)	(0.0057)
N	580256	903706	720457	763512	667650	816323	757067	726915	759887	724102
$Adj.R^2$	0.222	0.402	0.292	0.392	0.290	0.386	0.284	0.405	0.296	0.357
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B

	Ret_Open 1-day									
	Night_Like		Night_Favor		Night_Retweet		Night_Reply		Night_Follower	
	High	Low	High	Low	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Night_Sent	0.0440***	0.0025	0.0510***	-0.0244***	0.0689***	-0.0166**	0.0803***	-0.0308***	0.0465***	-0.0101
	(0.0104)	(0.0070)	(0.0091)	(0.0066)	(0.0093)	(0.0065)	(0.0086)	(0.0063)	(0.0079)	(0.0067)
N	564990	988510	629956	923551	544805	1008706	752652	800861	793704	759821
$Adj.R^2$	0.216	0.384	0.284	0.357	0.278	0.352	0.277	0.380	0.283	0.367
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 9: The effect of dissemination power on the investor sentiment's long-term return predictability

This table shows the effect of dissemination power on the long-term return predictability of intraday and overnight sentiment measures textually extracted from Xueqiu. Panel A shows the predictability for the close-to-close return of 2-day, 3-day, 1-week, -month, 3-month and 6-month windows. Panel B shows the predictability for the open-to-open daily return of 2-day, 3-day, 1-week, -month, 3-month and 6-month windows. All variables are defined in the Appendix. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A

	Likes		Favorites		Retweets		Replies		Account Followers	
	More	Less	More	Less	More	Less	More	Less	More	Less
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
					2-day					
Daytime_Sent	0.1318***	0.0444***	0.1010***	0.0311***	0.1164***	0.0365***	0.1687***	0.0169**	0.0870***	0.0624***
	(0.0125)	(0.0082)	(0.0111)	(0.0072)	(0.0115)	(0.0073)	(0.0112)	(0.0073)	(0.0101)	(0.0081)
					3-day					
Daytime_Sent	0.1377***	0.0436***	0.1059***	0.0293***	0.1231***	0.0331***	0.1750***	0.0099	0.0907***	0.0610***
	(0.0155)	(0.0096)	(0.0132)	(0.0087)	(0.0138)	(0.0089)	(0.0136)	(0.0087)	(0.0121)	(0.0099)
					1-week					
Daytime_Sent	0.1563***	0.0469***	0.1247***	0.0314***	0.1421***	0.0358***	0.1923***	0.0046	0.1065***	0.0642***
	(0.0199)	(0.0127)	(0.0175)	(0.0115)	(0.0184)	(0.0116)	(0.0177)	(0.0116)	(0.0157)	(0.0130)
					1-month					
Daytime_Sent	0.2010***	0.0271	0.1862***	-0.0021	0.2079***	0.0026	0.2284***	-0.0393	0.1599***	0.0395
	(0.0426)	(0.0270)	(0.0382)	(0.0254)	(0.0394)	(0.0250)	(0.0387)	(0.0253)	(0.0337)	(0.0286)
					3-month					
Daytime_Sent	0.1959**	0.0050	0.2242***	-0.0461	0.2743***	-0.0522	0.2310***	-0.0808*	0.2381***	-0.0461
	(0.0822)	(0.0457)	(0.0723)	(0.0447)	(0.0737)	(0.0447)	(0.0718)	(0.0428)	(0.0631)	(0.0492)
					6-month					
Daytime_Sent	0.3479***	0.1017	0.3557***	0.1146*	0.4213***	0.0748	0.3615***	-0.0051	0.3436***	0.0930
	(0.1154)	(0.0624)	(0.1003)	(0.0608)	(0.1026)	(0.0611)	(0.1000)	(0.0591)	(0.0896)	(0.0664)
N	580256	903706	720457	763512	667650	816323	757067	726915	759887	724102
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B

	Likes		Favorites		Retweets		Replies		Account Followers	
	More	Less	More	Less	More	Less	More	Less	More	Less
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
					2-day					
Night_Sent	0.0028	-0.0200**	0.0130	-0.0592***	0.0402***	-0.0562***	0.0712***	-0.0707***	0.0147	-0.0443***
	(0.0155)	(0.0099)	(0.0131)	(0.0096)	(0.0139)	(0.0094)	(0.0129)	(0.0089)	(0.0119)	(0.0094)
					3-day					
Night_Sent	-0.0268	-0.0304**	-0.0114	-0.0752***	0.0263	-0.0792***	0.0427***	-0.0810***	-0.0040	-0.0645***
	(0.0179)	(0.0123)	(0.0157)	(0.0116)	(0.0167)	(0.0116)	(0.0152)	(0.0109)	(0.0144)	(0.0114)
					1-week					
Night_Sent	-0.0524**	-0.0489***	-0.0341*	-0.0964***	-0.0014	-0.0985***	0.0146	-0.0964***	-0.0254	-0.0886***
	(0.0221)	(0.0147)	(0.0200)	(0.0137)	(0.0211)	(0.0140)	(0.0189)	(0.0132)	(0.0176)	(0.0143)
					1-month					
Night_Sent	-0.2915***	-0.1539***	-0.1612***	-0.2535***	-0.1485***	-0.2456***	-0.1416***	-0.2449***	-0.1887***	-0.2258***
	(0.0441)	(0.0297)	(0.0413)	(0.0271)	(0.0428)	(0.0273)	(0.0383)	(0.0282)	(0.0356)	(0.0301)
					3-month					
Night_Sent	-0.3989***	-0.2724***	-0.2690***	-0.3544***	-0.2495***	-0.3532***	-0.2067***	-0.4070***	-0.2557***	-0.3887***
	(0.0803)	(0.0485)	(0.0729)	(0.0459)	(0.0769)	(0.0467)	(0.0682)	(0.0468)	(0.0619)	(0.0507)
					6-month					
Night_Sent	-0.4719***	-0.2754***	-0.2745***	-0.3484***	-0.2820***	-0.3637***	-0.2020**	-0.4601***	-0.3591***	-0.3440***
	(0.1135)	(0.0643)	(0.1012)	(0.0634)	(0.1074)	(0.0633)	(0.0961)	(0.0634)	(0.0855)	(0.0682)
N	564990	988510	629956	923551	544805	1008706	752652	800861	793704	759821
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 10: The effect of dissemination power on the co-movement between investor sentiment and stock trading

This table shows the effect of dissemination power on the contemporaneous relation between investor sentiment measures textually extracted from Xueqiu and stock trading activities. Panel A shows the contemporaneous relationship between daytime sentiment and daytime return, Panel A shows the contemporaneous relationship between overnight sentiment and overnight return. All variables are defined in the Appendix. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A

	Ret_daytime									
	Likes		Favorites		Retweets		Replies		Account Followers	
	More	Less	More	Less	More	Less	More	Less	More	Less
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Daytime_Sent	0.7624***	0.4181***	0.5487***	0.5244***	0.5856***	0.4585***	0.7916***	0.3524***	0.5773***	0.4166***
	(0.0137)	(0.0075)	(0.0130)	(0.0076)	(0.0143)	(0.0072)	(0.0119)	(0.0064)	(0.0111)	(0.0070)
N	599848	1149140	678464	1070535	583641	1165355	803559	945452	873341	875676
$Adj.R^2$	0.230	0.373	0.274	0.351	0.272	0.350	0.287	0.370	0.288	0.365
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B

	Ret_overnight									
	Likes		Favorites		Retweets		Replies		Account Followers	
	More	Less	More	Less	More	Less	More	Less	More	Less
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Night_Sent	0.3049***	0.2197***	0.3311***	0.1726***	0.3402***	0.1779***	0.3396***	0.1690***	0.2840***	0.2188***
	(0.0070)	(0.0057)	(0.0069)	(0.0038)	(0.0072)	(0.0038)	(0.0071)	(0.0038)	(0.0060)	(0.0046)
N	603940	969821	755960	817794	698589	875165	785025	788735	804928	768842
$Adj.R^2$	0.222	0.342	0.269	0.326	0.266	0.324	0.261	0.342	0.278	0.307
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 11: Portfolio Analysis

This table shows the annualized returns and Sharpe ratio for the portfolios constructed based on the level of daytime sentiment, the level of overnight sentiment, the level of full day sentiment, the daily change in daytime sentiment, the daily change in overnight sentiment, the daily change in full day sentiment, and the difference between daytime and overnight sentiment. All the portfolios are daily rebalanced by buying the stocks with its sentiment measure in the 1st quintile and selling the stocks with its sentiment measure in the 5th quintile. The full sample is based on all stocks of Chinese A-share market and the investment period is from 2016/01/01-2020/12/31. Panel A presents the portfolios based on the market close-to-close trading strategy, and Panel B presents the portfolios based on the market open-to-open strategy.

Panel A

	Annualized Return (%)			
Round-trip Commissions	0%	0.01%	0.02%	0.03%
Daytime_Sent	49.05	42.01	35.30	28.90
(Sharpe Ratio)	(4.07)	(3.57)	(3.06)	(2.56)
Night_Sent	-2.99	-7.58	-11.95	-16.12
(Sharpe Ratio)	(-0.34)	(-0.80)	(-1.26)	(-1.73)
Day_Sent	58.24	50.76	43.64	36.85
(Sharpe Ratio)	(4.03)	(3.60)	(3.17)	(2.75)
ΔDaytime_Sent	29.75	23.62	17.77	12.20
(Sharpe Ratio)	(3.67)	(2.97)	(2.26)	(1.56)
ΔNight_Sent	16.02	10.53	5.30	0.32
(Sharpe Ratio)	(2.00)	(1.31)	(0.62)	(-0.07)
ΔDay_Sent	32.55	26.28	20.31	14.62
(Sharpe Ratio)	(3.41)	(2.81)	(2.21)	(1.60)
Δ(Daytime-Night)_Sent	38.50	31.95	25.71	19.77
(Sharpe Ratio)	(4.28)	(3.63)	(2.97)	(2.32)

Panel B

	Annualized Return (%)			
Round-trip Commissions	0%	0.01%	0.02%	0.03%
Daytime_Sent	8.94	3.79	-1.12	-5.80
(Sharpe Ratio)	(0.85)	(0.33)	(-0.18)	(-0.70)
Night_Sent	3.45	-1.44	-6.11	-10.55
(Sharpe Ratio)	(0.28)	(-0.18)	(-0.64)	(-1.10)
Day_Sent	29.25	23.14	17.32	11.77
(Sharpe Ratio)	(2.12)	(1.71)	(1.31)	(0.90)
ΔDaytime_Sent	3.52	-1.38	-6.05	-10.50
(Sharpe Ratio)	(0.38)	(-0.31)	(-0.99)	(-1.68)
ΔNight_Sent	0.38	-4.38	-8.90	-13.22
(Sharpe Ratio)	(-0.06)	(-0.75)	(-1.44)	(-2.13)
ΔDay_Sent	1.18	-3.61	-8.17	-12.52
(Sharpe Ratio)	(0.06)	(-0.45)	(-0.97)	(-1.48)
Δ(Night-Daytime)_Sent	-4.95	-9.45	-13.74	-17.82
(Sharpe Ratio)	(-0.85)	(-1.55)	(-2.25)	(-2.95)