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The relative importance of overnight sentiment versus trading-hour sentiment in volatility forecasting

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ABSTRACT

We examine the relative importance of overnight sentiment versus trading-hour sentiment in forecasting volatility. Previous studies on investor sentiment either ignore overnight sentiment or aggregate overnight sentiment with trading-hour sentiment. With the help of Chinese sentiment dictionary, we extract investor sentiment from Chinese internet social forums. Our empirical analyses suggest conclusively that investor sentiment significantly affects volatility. In particular, overnight sentiment is more informative than trading-hour sentiment in forecasting volatility, and has higher predictive power than overnight returns, which are widely used to capture overnight information. Our results hold in a series of robustness tests, including in highly volatile subsample, alternative rolling window size, and alternative sentiment proxy.

1. Introduction

Volatility is closely tied to risk management, asset pricing, and asset allocation. It is not surprising that numerous researchers devote much efforts to improve the forecasting accuracy of volatility. Various studies have constructed new and powerful predictors to forecast volatility. For example, Christiansen et al. (2012) show that credit risk, financing liquidity, and time-varying risk premium perform well as predictors of volatility. Paye (2012) find that the commercial paper-to-treasury spread, default return, default spread, and the investment-to-capital ratio can help forecast volatility. Engle et al. (2013) provide evidence that including economic fundamentals in the analyses, such as inflation and industrial production growth, can further improve volatility forecasting.

This paper builds on prior studies to improve volatility forecasting. Our study differs from most of the previous studies by focusing on investor sentiment and using a high frequency data to evaluate the significance and the robustness of the investor sentiment's forecasting power for volatility. We are inspired by a growing body of empirical literature that explores the relationship between investor sentiment and stock volatility (Brown, 1999; Lee et al., 2002; Ho et al., 2013; Behrendt and Schmidt, 2018; Audrino et al., 2020; Zhang et al., 2021; Gong et al., 2022). Lee et al. (2002) demonstrate that changes in bullish investors' sentiment are negatively related to volatility. Ho et al. (2013) find that news sentiment has a significant impact on the intraday volatility of individual U.S. stocks. Zhang et al. (2021) show that textual sentiment extracted from the social platform has predictive power on stock volatility. However, the relationship between investor sentiment and stock price volatility is far from conclusive. For example, Antweiler and Frank (2004) and Audrino et al. (2020) show that, while investor sentiment significantly improves the forecasting accuracy of the stock market volatility, the magnitudes of the improvements is relatively small. Similarly, Behrendt and Schmidt (2018) show that sentiment extracted from Twitter data is related to the intraday volatility, but the forecast improvements are not economically significant. Moreover, the direction of the causal relationship remains unclear. For instance, Wang et al. (2006) find that most of sentiment measures are caused by returns and volatility rather than vice versa.

An essential aspect of our investigation is that we decompose investor sentiment into overnight sentiment and trading-hour sentiment and examine the relative importance of the two in forecasting volatility. The answer to this question is important for understanding the source of investor sentiment's predictive power in stock market volatility. We posit that the factors driving sentiment are different in the trading period and overnight period. First, investor sentiment does not arise in a vacuum, and information is an important source of investor sentiment (Sibley et al., 2016). For example, investor sentiment is affected by monetary policy decisions (Kurov, 2010; Lutz, 2015), firm announcements (Barberis et al., 1998), and economic news (Shapiro

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et al., 2022). Although this does not mean that the reaction of investor sentiment to information is always rational, the fundamental source of investor sentiment's predictive power in stock market volatility may lie in information (Sibley et al., 2016). Second, a great deal of information is gathered overnight. While stock exchanges operate with specific trading hours, information in financial markets continuously changes and accumulates. The overnight period is becoming more important due to the integration of global financial markets and nighttime information announcements. As Chinese stock markets close, U.S. stock markets begin to trade. The stock price of Chinese stock markets may thus be affected by stock price developments in U.S. and global stock markets during the overnight period. Additionally, the announcement of macroeconomic policies, such as monetary policy, often occurs during non-trading-hours. For instance, during our sample period, the People's Bank of China made six interest rate adjustments and twelve deposit reserve ratio adjustments, all of which were announced between 17:00 p.m. and 20:00 p.m, except for one announcement to adjust the deposit reserve ratio. Consistent with these observations, Tsiakas (2008) suggests that the information accumulated overnight contains substantial predictive ability in European and U.S. stock market, and Tseng et al. (2012) demonstrates similar results for the Taiwanese stock market. Ahoniemi and Lanne (2013) find that a realized volatility estimator incorporating overnight information yields greater accurate. Third, there is evidence that overnight sentiment is news-driven and is less influenced by concurrent market price signals (Li et al., 2019), while trading-hour sentiment is price-driven. Many studies show that investor sentiment during the trading hours is greatly influenced by stock prices (e.g. (Wang et al., 2006; Kling and Gao, 2008)). This implies that the sentiment during trading hours on a given trading day may already be incorporated into the correspondence prices. Therefore, if the forecasting model (such as HAR-RV model) contains price information, the trading-hour sentiment may have limited additional information beyond what is already captured by the market trading data, thereby potentially limiting the forecasting performance. In contrast, overnight sentiment is more likely to contain new information that has not yet been reflected in prices. Consequently, it may hold more potential for forecasting volatility.

Our study makes three contributions. First, this paper contributes to the construction of investor sentiment proxy. Investor sentiment cannot be directly observed, and an important research question in empirical finance is to construct a good proxy for investor sentiment (Corredor et al., 2013). The existing literature mainly considers three measures of investor sentiment. The first is survey-based sentiment proxies, which collect investors' view in the form of questionnaires, such as the survey data of Chinese Central Television Station (Kling and Gao, 2008) and the consumer confidence index (Bathia and Bredin, 2013; Coakley et al., 2014). This measurement is subjective and may contain substantial noise. The formation of views requires respondents to spend time and effort. Without effective incentives, respondents may have weak motivation to complete the investigation. A further weakness is that it is impossible to have high-frequency sentiment data from surveys. The second is market-based sentiment proxies constructed from trading data, such as trading volume (Scheinkman and Xiong, 2003) and closed-end fund discount (Lee et al., 1991). The investor sentiment constructed by Baker and Wurgler (2006) based on the principal components of six market variables is the most widely used one. One limitation of market-based sentiment proxies is that they are influenced by the collective interplay of numerous economic variables, extending beyond investor sentiment alone (Da et al., 2015). Moreover, the market-based measures reflect only the investor sentiment during the trading period, overlooking the potential influence of investor sentiment during non-trading periods. The third are text-based sentiment proxies, which are constructed from millions of messages published on the internet. The literature generally concludes that investor sentiment developed by text-based analysis can predict stock returns (Xu et al., 2022; Cookson et al., 2023). Compared with the survey-based measure, the investor sentiment extracted from internet posting can be available in high-frequency. Unlike market-based proxies, this measure has the added advantage of capturing overnight investor sentiment as well. We adopt the dictionary-based method to quantify the intraday high frequency investor sentiment of the text messages. Dictionary-based approach is replicable and more transparent than the machine learning technique (Renault, 2017). The sentiment proxy developed in this paper has three characteristics. (1) In terms of dictionary selection, we use the Chinese financial market sentiment dictionary provided by Yao et al. (2021), which is more suitable for the analysis of informal texts than the translation of English dictionary. (2) Our sentiment measure is more comprehensive. In addition to using the dictionary to distinguish sentiment, we also consider the effects of emotional symbols, private words, adversative conjunctions, and rhetorical questions on investor sentiment identification. (3) Our sentiment measures are available at intraday hourly frequency. It is important to use high-frequency investor sentiment because the effect of investor sentiment on volatility may be short-lived (Chiu et al., 2018; Renault, 2017; Bonato et al., 2021). Da et al. (2015) point out that "High-frequency analysis of investor sentiment is found only in laboratory settings" (Da et al., 2015, page. 2).

Second, our paper contributes to the debate on whether investor sentiment can improve the performance of volatility forecasting. Our results provide strong and robust evidence that investor sentiment extracted from internet social media can indeed improve volatility forecasting performance, which is not only statistically significant (both in-sample and out-sample), but also economically large. This finding remains in highly volatile subsample, is robust to alternative sentiment proxy, alternative rolling window size, and the control of overnight returns. More importantly, we provide more insights into the source of the investor sentiment predictability. The investigation of the relationship between investor sentiment and stock price volatility has been largely empirical driven, and the source of the predictive power of investor sentiment on volatility remains unclear. By decomposing daily sentiment into overnight sentiment and trading-hour sentiment, we able to show which sentiment, overnight sentiment or trading-hour sentiment, has higher predictive power on stock market volatility. Overnight sentiment is either ignored or aggregated with trading-hours sentiment in existing literature. For example, market-based proxies for investor sentiment, such as turnover rate (Baker and Wurgler, 2006) and buy–sell imbalance (Kumar and Lee, 2006), rely only on trading-hour information. In intraday forecasting analyses, scholars often pay more attention to the sentiment during trading-hours (e.g., Sun et al., 2016; Renault, 2017; Broadstock and Zhang, 2019). We find that volatility forecasting power comes primarily from sentiment in non-trading-hours. This insight is useful in developing more informative investor sentiment proxy to predict stock returns or volatility in the future. More importantly, this finding is consistent with the interpretation that the predictive power of investor sentiment on volatility forecasting comes from overreaction of information. We elaborate on this point in Section 4.1.

Finally, while some of previous studies on volatility forecasting have paid attention to overnight information, most of them measure overnight information by overnight returns. For example, Ahoniemi and Lanne (2013), Wang et al. (2015), Kambouroudis et al. (2021), and Liang et al. (2021) employ overnight returns as overnight information proxy to extend HAR-RV model, and show that overnight returns have strong predictive power. There is evidence that overnight returns are a suitable proxy for measuring firm-specific sentiment in some countries (Aboody et al., 2018). In Chinese stock markets, the evidence is mixed. For example, Xiong et al. (2020) find that overnight returns are a good proxy for investor sentiment in U.S. stock markets, but less so in other markets. This is because there exist important differences between Chinese stock markets and other financial markets. First, Chinese stock markets imposed daily price limits on 16 December 1996 and have maintained the price limit rules for regular stocks until this day. Daily price limit rules may limit the ability of stock returns to reflect information or investor sentiment. Furthermore, Chinese stock markets are dominated by individual investors. It is widely understood that individual investors are the main source of sentiment trading. However, China's A-share markets open by call auction, during which there is little trading from individual investors, and this tendency continues in the late half-hour (Gao et al., 2019). Thus, overnight returns may not be effective in capturing investor sentiment in Chinese stock markets, due to the limited trading from individual investors in the opening sessions. We extract investor sentiment from messages posted on social platforms on internet, which contain active posts from individual investors throughout of the day. To the best of our knowledge, our study is the first to examine the volatility forecasting power of high-frequency overnight sentiment based on online posts. Our results suggest that the predictive power of overnight sentiment on volatility forecasting significantly exceeds that of overnight returns.

The rest of the paper proceeds as follows. Section 2 presents the methodology of the study. Section 3 explains the data used in the paper. The empirical results are provided in Section 4. Section 5 discusses robust tests. Finally, Section 6 concludes.

2. Methodology

2.1. Investor sentiment measurement

We use dictionary-based approach to construct investor sentiment, which is replicable and more transparent than the machine learning technique (Renault, 2017). The key to this approach is the sentiment dictionary. There are a few dictionaries available. For example, Tetlock (2007) and Da et al. (2015) use the Harvard IV-4 dictionary and the Lasswell Value dictionary to conduct investor sentiment. Du et al. (2022), Li et al. (2019), and Sun and Zeng (2022) have developed investor sentiment index based on dictionary approach with respect to Chinese stock market. Unfortunately, there is no well-accepted Chinese financial sentiment dictionary. One possible solution is to use the Chinese translated version of the financial dictionary created by Loughran and McDonald (2011) (see e.g., Li et al., 2019; Yang et al., 2022; You et al., 2018). Due to the differences between Chinese and English languages, this solution may not be ideal. Recognizing this weakness, Li et al. (2019) manually expand the Chinese translation of the financial dictionary of Loughran and McDonald (2011). Du et al. (2022) further develop a Chinese financial sentiment dictionary from Chinese-language news articles. Both works highlight the importance of using a Chinese dictionary when discussing the relationship between the Chinese stock market and investor sentiment. As stated earlier, majority of investors in Chinese stock markets are individual households, and they express their sentiment in online social platforms. Posts on investor online forums for stocks are mostly informal texts, different from the language style used in formal documents. Taking these considerations into account, in this paper, we use sentiment words provided by Yao et al. (2021), which is a Chinese sentiment dictionary in the financial field suitable for internet social platforms, and they show that investor sentiment constructed based on this dictionary can effectively predict Chinese stock market returns.

To extract textual sentiment of messages posted on investor online forums, we conduct the analysis with the following five steps. First, the sentiment of a post is identified as positive or negative by the emotional symbols. If a post contains happy (unhappy) emotion symbols, the post is defined as positive (negative) sentiment. If a post contains both positive and negative emotion symbols, emotional symbols are ignored and the sentiment of the post is recognized by text. Second, privative words in Chinese can change sentiment polarities. The emotional polarity of words that appear after the privative words is reversed if the number of privative words is odd. The emotional polarity of words that appear after two privative words (i.e., double denial) remain unchanged. Third, Chinese adversative conjunction is used to express opposite conjunctive relation. Such a sentence usually consists of two parts separated by commas. According to Chinese language habits, the former part (before commas) generally represents objective facts, while the latter part (behind commas) contains the real sentiment expressed. Therefore, we only recognize the sentiment of words behind commas if adversative conjunction appears in a message text. Fourth, the use of Chinese rhetorical question is to strengthen tone, so as to express more intense reversed sentiment. Therefore, the sentiment polarities of the words behind the rhetorical markers are reversed if the post includes rhetorical markers. Finally, all texts are recognized as positive or negative sentiment based on Chinese sentiment dictionary of Yao et al. (2021).[1]

We construct intraday investor sentiment by subtracting the number of negative sentiment words (emotional symbols) from the number of positive sentiment words (emotional symbols) in a specific time interval. The overnight sentiment ($\mathrm{NS_t}$) is the sum of the value from 15:00 p.m. (i.e., the closing time) on a trading day to 9:25 a.m. (i.e., the opening time) on the next trading day. According to this definition, the weekend and holiday sentiment is included in $\mathrm{NS_t}$. For example, June 2, 2014 is Chinese traditional Dragon Boat Festival. May 31, 2014 to June 2, 2014 are non-trading days. To predict volatility on June 3, 2014, overnight sentiment counts from 15:00 p.m. on May 30, 2014 to 9:25 a.m. on June 3, 2014. The trading-hour sentiment ($\mathrm{TS_t}$) is the sum of the value from 9:30 a.m. to 15:00 p.m. on a trading day, which correspond to the regular trading hours in Chinese stock markets. The daily sentiment ($\mathrm{DS_t}$) is the sum from 0:00 a.m. to 24:00 p.m. on a day.

2.2. Forecasting models

Following Corsi (2009), we use HAR-RV model to conduct volatility forecasting analyses. The daily realized variance is the sum of squares of intraday returns

$$RV_t = \sum_{i=1}^{N} r_{t,i}^2, \tag{1}$$

where N is the observed number of the intraday returns. $r_{t,i}$ is the 5-min intraday returns at time i on day t. The square root of realized variance is the realized volatility. Following Ahoniemi and Lanne (2013) and Liu et al. (2018), in what follows, the term realized volatility refers to both the realized variance and its square root. The weekly realized volatility (RVW) and the monthly realized volatility (RVM) are defined respectively as follows

$$RVW_t = \frac{1}{5}\sum_{i=0}^{4} RV_{t-i}, \tag{2}$$

[1] The data is available on the web: https://gitee.com/arlionn/SentimentDictionaries/blob/master.

$$RVM_t = \frac{1}{22}\sum_{i=0}^{21} RV_{t-i}. \tag{3}$$

A standard HAR-RV model form is

$$RV_{t+1} = \beta_0 + \beta_1 RV_t + \beta_2 RVW_t + \beta_3 RVM_t + \varepsilon_{t+1}, \tag{4}$$

The effect of investor sentiment on volatility may be short-lived (Chiu et al., 2018; Renault, 2017; Bonato et al., 2021). Therefore, we focus on short-horizons (one-day-ahead) volatility forecasting. To examine the role of sentiment variables on volatility forecasting, we add the lagged sentiment variables to volatility forecasting model.

$$RV_{t+1} = \beta_0 + \beta_1 RV_t + \beta_2 RVW_t + \beta_3 RVM_t + \beta_4 NS_t + \varepsilon_{t+1}, \tag{5}$$

$$RV_{t+1} = \beta_0 + \beta_1 RV_t + \beta_2 RVW_t + \beta_3 RVM_t + \beta_4 TS_t + \varepsilon_{t+1}, \tag{6}$$

$$RV_{t+1} = \beta_0 + \beta_1 RV_t + \beta_2 RVW_t + \beta_3 RVM_t + \beta_4 DS_t + \varepsilon_{t+1}, \tag{7}$$

where NS, TS, and DS represent overnight sentiment, trading-hour sentiment and daily sentiment, respectively. For convenience, the above three volatility forecasting model are denoted as HAR-RV-NS, HAR-RV-TS, and HAR-RV-DS.

2.3. Out-of-sample analysis

To explore the out-of-sample forecasting performances of our models, we conduct a rolling window regression analysis. To quantitatively evaluate the forecasting accuracy, we use the following popular loss function

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\sigma_i^2 - \hat{\sigma}_i^2)^2, \tag{8}$$

where MSE is the mean squared forecast errors, σ_i^2 is the actual RV, and $\hat{\sigma}_i^2$ is the forecast. Following Campbell and Thompson (2008), the out-of-sample $R^2(R^2_{os})$ is defined as

$$R^2_{OS} = 100 \times (1 - \frac{MSE_{test}}{MSE_{bench}}), \tag{9}$$

where MSE_{test} and MSE_{bench} are the mean squared forecast errors of the tested model and the benchmark model respectively. A positive R^2_{OS} shows that the mean squared forecast errors of the tested model is less than those of the benchmark model. The Clark and West (2007) method (hereafter CW) is employed to test the significance of R^2_{OS}. Clark and West (2007) propose a series of forecasting loss differences between the tested and benchmark models as

$$F_t = (RV_t - \hat{R}V_{bench,t})^2 - (RV_t - \hat{R}V_{test,t})^2 + (\hat{R}V_{bench,t} - \hat{R}V_{test,t})^2. \tag{10}$$

By regressing F_t on a constant, the CW statistic is the t-statistic of the constant, which is an approximately standard normal asymptotic distribution.

2.4. Economic value

To evaluate the economic value of volatility forecasting, we follow Wang et al. (2006) and Neely et al. (2014) by considering a mean variance utility investor who allocates the assets between stock index and risk-free asset. The investor's optimal weight on stock index on day t is given by:

$$W_t^* = \frac{1}{\gamma}(\frac{\hat{r}_{t+1}}{\hat{\sigma}_{t+1}}), \tag{11}$$

where $\hat{r}_{t+1}$ and $\hat{\sigma}_{t+1}$ are the mean and volatility forecasts of stock excess returns, respectively. The above described models are implemented to generate $\hat{\sigma}_{t+1}$. Welch and Goyal (2008) argue that the out-of-sample forecasting performance of most variables does not exceed prevailing historical means. We therefore use historical average model to generate $\hat{r}_{t+1}$. We restrict the optimal weight between 0 and 1, implying no short-selling and no leverage trading. The portfolio returns at day t + 1 is:

$$R_{t+1} = W_t^* r_{t+1} + r_{f,t+1}. \tag{12}$$

Two criteria, i.e., certainty equivalent return (CER) and Sharpe ratio (SR), are used to evaluate economic performance of volatility forecasting model.

The CER for the portfolio is

$$CER_P = \hat{\mu}_P - \frac{1}{2}\gamma\hat{\sigma}_P^2, \tag{13}$$

where $\hat{\mu}_P$ and $\hat{\sigma}_P^2$ are the mean and variance of portfolio returns over the out-of-sample period, respectively. γ is the relative risk aversion coefficient.

The SR for the portfolio is

$$SR = \frac{\overline{\mu}_P}{\overline{\sigma}_P}, \tag{14}$$

where $\overline{\mu}_P$ and $\overline{\sigma}_P$ are the mean and standard deviation of portfolio excess returns, respectively.

3. Data

The messages posted on Eastmoney, which is a largest internet social forum for stocks in China, are collected as our sample. To construct the corresponding market-level sentiment index, we collect messages posted on Shanghai Securities Composite Index message board of Eastmoney from January 1, 2014 to December 31, 2022. As explained in the introduction, we distinguish overnight sentiment from trading-hour sentiment. We argue that the overnight sentiment is different from the trading-hour sentiment. The former is more information driven, while the latter is more affected by the concurrent trading prices. As an example, Table S1 and Table S2 in the appendix list a part of investor postings during non-trading-hours and trading-hours, which is aim to illustrate the different source of sentiment. For instance, at 16:55 p.m. on June 27, 2015 (Friday), the People's Bank of China announced the reduction of deposit reserve ratio on its website. Affected by the news, investor sentiment generally became optimistic during overnight (as shown in Table S1). However, the stock market fell all the way after opening on Monday (June 29, 2015). As a result, investor sentiment became pessimistic during Monday's trading-hours (as shown in Table S2).

The realized volatility of stock index (Shanghai Stock Exchange Composite Index, i.e., SSEC) is collected from CSMAR. Fig. 1 depict the evolution of realized volatility, trading-hour sentiment, and overnight sentiment in our sample periods, respectively. Table 1 lists descriptive statistics of stock market index RV and investor sentiment. It shows that the mean realized volatility of SSEC index is 1.248%, and standard deviation is 2.782%. The mean of the sentiment variables is negative, implying that investor sentiment is generally negative in the sample period. The daily sentiment (DS) is the lowest among different sentiment variables, while the overnight sentiment (NS) is the highest. The daily sentiment (DS) is close to trading-hour sentiment (TS).

To assess the validity of investor sentiment constructed in this paper, we first develop the monthly investor sentiment measure, i.e., MS_t by subtracting the number of negative sentiment words from the number of positive sentiment words in month t. Then, following Sun et al. (2016), we run the following regression,

$$MS_t = \beta_0 + \beta_1 PS_t + \varepsilon_t, \tag{15}$$

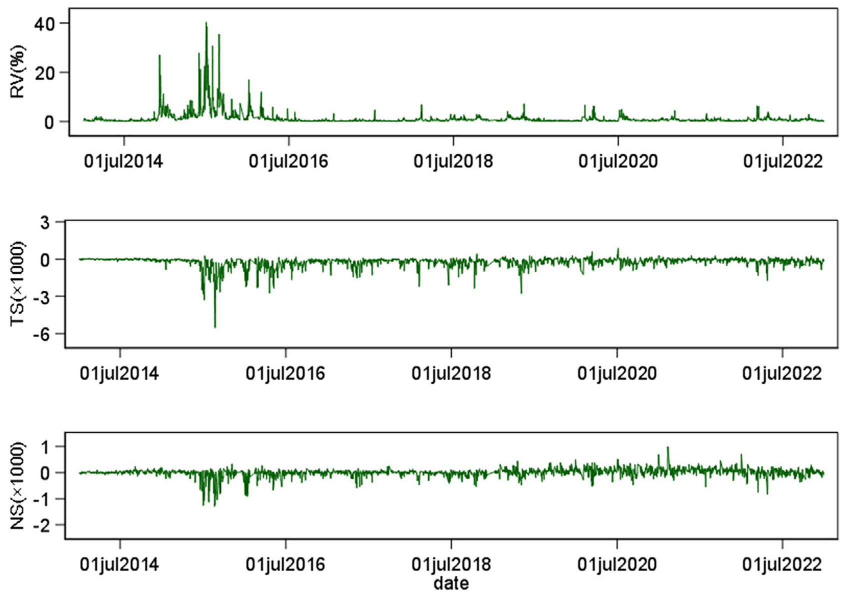

Fig. 1. Realized volatility, trading-hour sentiment, and overnight sentiment: January 2, 2014–December 31, 2022.

Table 1
Descriptive statistics.

Variables	Mean	Std. deviation	Min.	Max.
RV (%)	1.248	2.782	0.068	40.31
DS ($\times 10^3$)	−0.243	0.497	−6.484	1.315
TS ($\times 10^3$)	−0.227	0.391	−5.518	0.875
NS ($\times 10^3$)	−0.007	0.161	−1.289	0.988

Note: This table lists descriptive statistics of stock market index RV and investor sentiment. RV is realized volatility of Shanghai Stock Exchange Composite Index. We construct intraday investor sentiment by subtracting the number of negative sentiment words (emotional symbols) from the number of positive sentiment words (emotional symbols) in a specific time interval. The overnight sentiment (NS_t) is the sum from 15:00 p.m. on trading day t to 9:25 a.m. on new trading day t + 1. The trading-hour sentiment (TS_t) is the sum from 9:30 a.m. to 15:00 p.m. on trading day t, which correspond to the regular trading-hours in China's stock market. The daily sentiment (DS_t) is the sum from 0:00 a.m. to 24:00 p.m. on trading day t.

where PS_t is an alternative investor sentiment proxy at month t. A composite investor sentiment index and three single proxy variables are used as *PS*. The three proxy variables are consumer confidence index (CCI), the number of newly opened investor accounts (NA), and the number of IPOs (IPON). We also employ the method proposed by Baker and Wurgler (2006) to develop the composite investor sentiment index (CIS), which is constructed from the six variables based on their first principal component. The six variables include the closed-end fund discount, the number of IPOs, the average first-day returns on IPOs, the market turnover rate, consumer confidence index, and the number of newly opened investor accounts. The regression results are reported in Table 2. All t-statistics are adjusted according to Newey and West (1987). As we can see from Table 2, the relations between MS and alternative proxies are statistically significant and positive at the 5% level or stronger. Taken together, the results support the use of MS as investor sentiment. Note however that, the above four alternative investor sentiment proxies are available only monthly or weekly. In contrast, our sentiment measure is available in higher frequency. Moreover, we can decompose this sentiment into trading-hour and non-trading-hour sentiment.

Table 2
The relation between MS and existing sentiment proxies.

Variables	(1) MS	(2) MS	(3) MS	(4) MS
CIS	0.308***			
	(3.57)			
IPON		0.100***		
		(2.94)		
CCI			0.126**	
			(2.30)	
NA				4.883***
				(2.86)
Constant	−18.310***	−7.181***	−18.812***	−4.699***
	(−4.74)	(−6.91)	(−3.04)	(−7.86)
R-squared	0.107	0.075	0.048	0.072

Notes: MS is the monthly investor sentiment measure, which is constructed by subtracting the number of negative sentiment from the number of positive sentiment at month t. CCI is consumer confidence index, NA is the number of newly opened investor accounts, and IPON is the number of IPOs. We use principal component analysis to develop a composite investor sentiment index (CIS), which is constructed from the closed-end fund discount, the number of IPOs, the average first-day returns on IPOs, the market turnover rate, consumer confidence index, and the number of newly opened investor accounts. Newey and West (1987) adjusted t-statistics are listed in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% level.

4. Empirical results

The sentiment effects on stock market returns and realized volatility are short-lived (Chiu et al., 2018; Renault, 2017; Bonato et al., 2021; Kim and Ryu, 2021). Therefore, this paper focus on short-run forecast horizons. We report and discuss results in three steps. First, we perform in-sample analysis. Second, we conduct out-of-sample analysis through the rolling window prediction method. Finally, we assess the economic values.

4.1. In-sample analysis

This section analyzes the results of regression models over the entire sample period. Table 3 shows the results of in-sample regressions. We observe that the RV, RVW, and RVM have significant effects on stock realized volatility, which is consistent with earlier studies (Xiao et al., 2021; Liang et al., 2020). Our focus is on the relation between investor sentiment and realized

Table 3
In-sample daily regression results.

Variables	(1) RV_{t+1}	(2) RV_{t+1}	(3) RV_{t+1}	(4) RV_{t+1}
RV	0.268***	0.235***	0.243***	0.233***
	(10.27)	(8.98)	(9.26)	(9.12)
RVW	0.492***	0.467***	0.474***	0.452***
	(12.31)	(11.79)	(11.91)	(11.57)
RVM	0.145***	0.129***	0.131***	0.132***
	(4.10)	(3.68)	(3.73)	(3.83)
DS		−0.720***		
		(−7.77)		
TS			−0.728***	
			(−6.22)	
NS				−3.040***
				(−11.21)
Constant	0.118**	0.037	0.024	0.207***
	(2.43)	(0.75)	(0.48)	(4.32)
R-squared	0.54	0.56	0.55	0.57

Note: This table reports in-sample regression results. RV, RVW, and RVM is the daily, weekly and monthly realized volatility. NS is overnight sentiment, TS is trading-hour sentiment, and DS is daily sentiment. T-statistics are listed in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% level.

volatility. Table 3 shows that investor sentiment has a negative and significant effect on volatility for one-day-ahead forecasting, which indicates the realized volatility rise when sentiment becomes more negative. This result is consistent with the findings of Liang et al. (2020), who document a negative forecasting effect of investor sentiment on SSEC realized volatility. The negative effect of investor sentiment on realized volatility is also consistent with Bonato et al. (2021), who shows that realized volatility is negatively correlated with investor sentiment measured by happiness index in gold market. Lee et al. (2002) also shows that investor sentiment is negatively linked to volatility in US stock markets, with volatility increasing (decreasing) when sentiment becomes pessimistic (optimistic).

We aim to distinguish the different predictive power of TS and NS. To do so, we perform two analyses. First, we compare the regression coefficients and illustrate their economic significance by the relative change of the standard deviation. The estimated coefficients for TS and NS are −0.728 and −3.040 for one-day-ahead forecasting. The coefficient of −0.728 on TS implies that increasing TS by one standard deviation (here 0.391) would reduce 23% of the mean of RV or 10% of the standard deviation of RV. In contrast, the coefficient −3.040 for NS implies that increasing NS by one standard deviation (0.161) would reduce RV by 39% of the mean or 18% of the standard deviation of RV. Therefore, in terms of economic significance, the former is only about half of the latter. Interestingly, the effect of DS on RV is also less than that of NS. Increasing DS by one standard deviation (0.497) would reduce 29% of the mean of RV or 13% of the standard deviation of RV. This result suggests that, by aggregating the overnight and trading-hour sentiment, the forecasting ability of sentiment for volatility is even diluted. Second, the R^2 of HAR-RV increases from 54% to 56% when we include DS. However, the R^2 decreases slightly when we use TS instead of DS, from 54% to 55%, suggesting that the forecast performance becomes weaker when we use TS only. Finally, when we use NS instead of DS, the R^2 increases from 54% to 57%. These results show that the primary forecasting ability of sentiment on volatility comes from NS. The goodness of fit of the model improves only slightly when we include the daily sentiment and trading-hour sentiment. In contrast, when overnight sentiment is added to HAR-RV model, the goodness of fit increases by 6%.

To further examine the role of overnight sentiment, we perform a series of intraday hourly regression. First, we define hourly realized volatility:

$$RV_{j,t} = \sum_{i=1}^{m} r_{i,j,t}^2, \tag{16}$$

where m is the observed number of the intraday hourly 5-min returns, i.e., $m = 12$. $r_{i,j,t}$ is the 5-min returns. The square root of realized variance is realized volatility, $j = 1, 2, 3$, and 4 represent four trading hours. The hourly regression model is as follows:

$$RV_{j,t} = \beta_0 + \beta_1 NS_t + \delta_1 ST_{j-1,t} + \lambda_l \sum_{l=1}^{L} RV_{j-l} + \varepsilon_{j,t} \tag{17}$$

where $RV_{j,t}$ is jth hourly realized volatility on day t. We use the lagged 8 hours' realized volatility (namely $L = 8$) as the control variable. NS remains as overnight sentiment. $ST_{i,t}$ ($i = 1, 2, 3$) represents intraday ith hour's trading sentiment on day t.

Table 4 reports the hourly regression results. As we can see, overnight sentiment has a significant and negative impact on the realized volatility of the subsequent hour, and all coefficients are statistically significant at the 1% level. In contrast, investor sentiment in the first hour of the trading session has no significant impact on the realized volatility of the subsequent hour. Investor sentiment in the second hour and third hour has significant impact on the realized volatility of the subsequent hour, but both sentiment measures do not provide extra information for the prediction of the realized volatility of the subsequent hour when they are controlled for the overnight sentiment. The R^2s hardly change. For example, the R^2 in column (4) is 0.738, and the R^2 in column (7) is 0.740. The difference between the two columns lies only in whether the sentiment of the third hour trading period is included.

In conclusion, the in-sample regression results show that investor sentiment significantly affects SSEC index volatility. More importantly, the effect of overnight sentiment is greater than that of trading-hour sentiment and daily sentiment. The results suggest that overnight sentiment, rather than trading-hour sentiment, plays a critical role in volatility forecasting. Sibley et al. (2016) indicate that investor sentiment can predict returns because investor sentiment contains information related to economic fundamentals. In light of this reasoning, the predictive power of overnight sentiment on volatility forecasting may arise from the novel information that is not yet incorporated into trading prices. In contrast, the sentiment during trading hours is more affected by trading prices. This explains the limited predictive power of trading-hour sentiment. This also explains that daily sentiment, which aggregates from overnight sentiment and trading-hour sentiment, has lower predictive power than overnight sentiment because the essential information is diluted by including trading-hour sentiment.

Furthermore, we explain theoretically and empirically why investor sentiment can predict volatility based on behavioral finance theory. In the traditional financial theoretical model, these noise traders are independent of each other, so all kinds of noise will eventually be offset by each other, without affecting the market price. In noise-trader theory, irrational investors acting coherently on a noisy signal, and the risk caused by noise-trader is systematic risk. De Long et al. (1990) believes that in the real world, the presence of noise traders can profoundly affect asset prices, and their biases in estimating asset values will be reflected in the prices, which is known as noise trader risk. This risk cannot be eliminated by arbitrageurs due to the limits of arbitrage. Investor sentiment can be used as a proxy for noise trading, thus investor sentiment should be correlated with volatility (Brown, 1999).

Investor sentiment does not arise out of thin air. The information shock is an important reason for sentiment generation.

Table 4
In-sample hourly regression results.

Variables	(1) RV_1	(2) RV_2	(3) RV_3	(4) RV_4	(5) RV_2	(6) RV_3	(7) RV_4
NS	−0.637***	−0.100***	−0.158***	−0.361***	−0.112***	−0.107***	−0.287***
	(−10.10)	(−3.75)	(−5.93)	(−13.79)	(−3.82)	(−3.60)	(−9.30)
ST_1					0.052		
					(0.99)		
ST_2						−0.195***	
						(−3.92)	
ST_3							−0.232***
							(−4.46)
Constant	0.156***	0.076***	0.006	0.024***	0.077***	0.004	0.018**
	(8.63)	(10.01)	(0.82)	(3.23)	(10.06)	(0.46)	(2.37)
$\sum_{l=1}^{L} RV_{j-l}$	Control	Control	Control	Control	Control	Control	Control
R-squared	0.458	0.624	0.682	0.738	0.624	0.684	0.740

Note: This table reports in-sample hourly regression results. RV_j is jth hourly realized volatility. ST_j is jth hourly investor sentiment. NS is overnight sentiment. RV_{j-l} represent lagged realized volatility. T-statistics are listed in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% level.

Table 5
Testing the overreaction hypothesis.

Variables	(1) RV_{t+1}	(2) RV_{t+1}	(3) RV_{t+1}	(4) RV_{t+1}	(5) RV_{t+1}	(6) RV_{t+1}	(7) RV_{t+1}	(8) RV_{t+1}
	Overreaction				Non-overreaction			
RV	0.242***	0.218***	0.224***	0.220***	0.368***	0.321***	0.336***	0.309***
	(5.36)	(4.88)	(4.99)	(5.07)	(9.57)	(7.96)	(8.33)	(7.87)
RVW	0.524***	0.472***	0.483***	0.440***	0.339***	0.371***	0.362***	0.376***
	(7.39)	(6.72)	(6.84)	(6.38)	(5.86)	(6.37)	(6.20)	(6.55)
RVM	0.152**	0.125*	0.130*	0.117*	0.157***	0.148***	0.149***	0.151***
	(2.13)	(1.77)	(1.83)	(1.70)	(4.09)	(3.87)	(3.89)	(3.97)
DS		−0.919***				−0.389***		
		(−4.93)				(−3.75)		
TS			−0.944***				−0.340***	
			(−4.00)				(−2.62)	
NS				−4.276***				−1.671***
				(−7.39)				(−6.07)
Constant	0.135	−0.039	−0.038	0.227	0.138***	0.093**	0.093**	0.179***
	(0.92)	(−0.26)	(−0.25)	(1.60)	(3.45)	(2.24)	(2.15)	(4.46)
R-squared	0.541	0.559	0.553	0.579	0.480	0.485	0.482	0.492

Note: RV, RVW, and RVM is the daily, weekly and monthly realized volatility. NS is overnight sentiment, TS is trading-hour sentiment, and DS is daily sentiment. If the absolute value of the overnight returns on the day is greater than sample mean, we define it as investors' overreaction to new information. Otherwise, we view it as non-overreaction. T-statistics are listed in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% level.

Investor sentiment is easily influenced by many economic factors and generates economic sentiment (Shapiro et al., 2022), and influenced by noneconomic factors, leading to sentiment such as the COVID-19 (Hasan, 2022). Drawing on the rational economic man hypothesis, as the decision-maker, investors can handle new information correctly and can make the best decisions. However, investors often exhibit irrationality and lack the ability to absorb new information correctly. According to behavioral finance theory, investors tend to overreaction when facing sudden or unexpected events, thereby causing an over rise or over fall in stock prices. Therefore, we argue that investor sentiment has a significant impact on stock volatility due to over-reaction to new information.

Empirically, we focus on overnight returns to test the overreaction hypothesis as an explanation for how investor sentiment impacts price volatility. Firms announcements and major economic news are frequently released at overnight. Investors' reactions to such information are reflected in overnight returns because there is no trading to reflect the information during overnight sessions (Ham et al., 2022). Thus, we use absolute value of overnight returns to proxy investor reaction to information shocks. The higher the absolute value of overnight returns, the stronger the investor's reaction to new information. If the absolute value of the overnight returns on the day is greater than its sample mean, we define it as investors' overreaction to new information. Otherwise, we view it as non-overreaction. Therefore, we expect that investor sentiment has a more significant impact on volatility in the overreaction sample than in the non-overreaction sample. Table 5 reports the results. Table 5 shows that the coefficient of NS in overreaction sample is −4.276, and the coefficient of NS in non-overreaction sample is −1.671. The former is 1.6 times higher than the latter. In the overreaction sample, when the investor sentiment variable is added to the HAR-RV model, the R^2 has increased significantly. For example, the R^2 of the model including overnight sentiment increases from 0.541 to 0.579. However, in the non-overreaction sample, when the investor sentiment variables are added to the HAR-RV model, the R^2s change little. This result indicates that the degree of investor response to information affects the impact of sentiment on volatility.

4.2. Out-of-sample analysis

To evaluate the out-of-sample forecasting performance, the volatility forecasts are calculated with a rolling window approach. In line with the existing literature, we select 200 as the scrolling window size for evaluating the out-of-sample forecasting performance. Based on this choice, we have 1,945 out-of-sample rolling-window forecasts from October 30, 2014 to December 31, 2022. In robustness checks, we use 100, 300, 500, and 800 as alternative sizes of rolling window.

Table 6 reports the out-of-sample forecasting performance. As we can see from Table 6, the accuracy of volatility forecasting is improved when investor sentiment is included in the HAR-RV

Table 6
Out-of-sample forecasting performance (one-day-ahead).

Tested model	Benchmark model	R^2_{os}(%)	CW	*p*-value
HAR-RV-DS	HAR-RV	11.192	2.008	0.022
HAR-RV-TS	HAR-RV	9.460	1.708	0.043
HAR-RV-NS	HAR-RV	13.399	2.753	0.003
HAR-RV-NS	HAR-RV-DS	2.484	2.147	0.015
HAR-RV-NS	HAR-RV-TS	4.349	2.207	0.013

Note: This table reports out-of-sample forecasting performance. NS is overnight sentiment, TS is trading-hour sentiment, and DS is daily sentiment. The rolling window for out-of-sample forecasting is 200.

Table 7
Results of MCS tests.

	MSE		HMSE		HMAE	
	T_R	T_{SQ}	T_R	T_{SQ}	T_R	T_{SQ}
HAR-RV	0.676	0.689	0.991	0.991	0.805	0.784
HAR-RV-DS	0.992	0.993	0.216	0.222	0.689	0.686
HAR-RV-TS	0.888	0.877	0.246	0.248	0.788	0.777
HAR-RV-NS	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
HAR-RV-OR	0.763	0.765	0.247	0.238	0.303	0.301
HAR-RV-ORS	0.965	0.960	0.991	0.991	0.788	0.777
HAR-RV-Lev	0.965	0.960	0.101	0.097	0.272	0.239

Notes: This table reports the *p*-values of MCS tests based on 5,000 block bootstraps. Two test statistics, i.e., range statistic (T_R), and semi-quadratic statistic (T_{SQ}), are employed. MSE, HMSE and HMAE are three loss functions. NS is overnight sentiment, TS is trading-hour sentiment, and DS is daily sentiment. OR is overnight return, ORS is absolute overnight return, and $Lev = \min(OR, 0)$. The numbers in bold denote that the corresponding model has the lowest loss function.

model. When HAR-RV is used as a benchmark while HAR-RV-DS, HAR-RV-TS, and HAR-RV-NS is used as tested model, the R^2_{os} are all significantly positive. There are some differences. First, the R^2_{os} is largest for HAR-RV-NS versus HAR-RV. Second, the CW tests show that the significance of these three cases is inconsistent. For HAR-RV-DS versus HAR-RV and HAR-RV-TS versus HAR-RV, the significance level is at 5%, while it is 1% for HAR-RV-NS versus HAR-RV. These results mean that the HAR-RV-NS model has the lowest prediction error. To further compare the out-of-sample predictive power of overnight sentiment versus trading-hour sentiment and daily sentiment, we take HAR-RV-NS as the tested model and HAR-RV-TS (and HAR-RV-DS) as the benchmark model to calculate R^2_{os} and CW. The results show that R^2_{os} is still positive and statistically significant at 5% level.

Similar to us, Liang et al. (2020) investigate the predictive ability of sentiment index constructed by social media, newspaper, and internet media news to forecast the realized volatility of Chinese stock markets. Liang et al. (2020) show a maximum out-of-sample R^2 of 6.16% for their HAR-RV model when using the HAR-RV model as the benchmark. Our out-of-sample R^2 is 13.399% in terms of overnight sentiment.

In short, the out-of-sample prediction results are consistent with the in-sample regression results. First, investor sentiment can indeed improve the prediction accuracy of RV. Second, overnight sentiment has the largest predictive power on future RV.

4.3. MCS test

To further examine which model produces better prediction accuracy, we use the model confidence set (MCS) developed by Hansen et al. (2011). Following Hansen et al. (2011), and Kambouroudis et al. (2021), two test statistics, range statistic (T_R), and semi-quadratic statistic (T_{SQ}), are employed. In addition to MSE, we also use HMSE and HMAE as loss function, which are defined as follows,

$$HMSE = \frac{1}{n}\sum_{i=1}^{n}(1-\hat{\sigma}_i^2/\sigma_i^2)^2, \tag{18}$$

$$HMAE = \frac{1}{n}\sum_{i=1}^{n}\left|1-\hat{\sigma}_i^2/\sigma_i^2\right|, \tag{19}$$

where σ_i^2 is the actual RV, and $\hat{\sigma}_i^2$ is the forecast.

Table 7 lists the results of MCS test. The *p*-values are obtained by 5,000 block-bootstraps. The larger the *p*-value, the better prediction accuracy of the corresponding model. Following Hansen et al. (2011), we use the significant level of 10%. Table 7 shows that HAR-RV-NS always generate volatility forecasts with a lower loss function than other models. This result suggests that the NS is a stronger factor for predicting future RV than TS and DS. Therefore, from statistical point of view, we conclude that overnight sentiment has more powerful predictability than the trading-hour sentiment.

4.4. Economic values

We use the interest rate of one-year treasury bonds as the risk-free interest rate. Following Neely et al. (2014) and Dai et al. (2021), the CER gains are calculated as the difference between the CER generated by the tested model and the CER generated by benchmark model. Here, the benchmark model is HAR-RV and the tested models are HAR-RV-DS, HAR-RV-TS and HAR-RV-NS, respectively. Therefore, the CER gains can be interpreted as investor's willing to pay to accessing the HAR-RV-DS (or HAR-RV-TS, HAR-RV-NS) model's forecasts instead of HAR-RV model's forecasts.

Table 8 shows the results of economic values. The annualized CER gains and SR generated by the HAR-RV-NS model are the largest. For example, when the relative risk aversion coefficient is 9, the CER gains for HAR-RV-NS is 3.435%. In contrast, the CER gains for HAR-RV-DS and HAR-RV-TS are 0.578% and 0.732%, respectively. The SR for HAR-RV-NS is 0.049, while the SR for HAR-RV-DS (HAR-RV-TS) is about 0.03. Similar results are found when the relative risk aversion coefficient is set to 6 or 3. Therefore, we conclude that overnight sentiment can achieve substantially economic gains, and the predictive power of overnight sentiment contain more information than trading-hour sentiment and daily sentiment.

5. Robustness checks

We perform a series of robustness checks in this section, including restricting our analysis to a highly volatile subsample and the pandemic period subsample, changing rolling window size, and using alternative sentiment proxies. We further construct HAR-RV model with overnight returns to test whether the predictive power of overnight sentiment is affected by the inclusion of overnight returns.

5.1. Highly volatile subsample

The Chinese A-shares market experienced a turbulence in 2015. On the first trading day of the year (January 5, 2015), A-shares opened at 3,258 points, and rose all the way up and reached 5,178 points on June 12, 2015, rising nearly 60% in 6 months. But, A-shares declined sharply in the second half of 2015 and the beginning of 2016, falling to the lowest point of 2,647 on January 28, 2016. We examine whether the prediction power of overnight investor sentiment for volatility remains robust during this highly volatile period. We restrict our sample to January 5, 2015 and January 28, 2016.

Table 8
Economic values.

	CER (%)			SR		
γ	HAR-RV-DS	HAR-RV-TS	HAR-RV-NS	HAR-RV-DS	HAR-RV-TS	HAR-RV-NS
3	−0.556	−0.177	1.601	0.019	0.021	0.027
6	0.661	0.583	3.546	0.022	0.022	0.036
9	0.578	0.732	3.435	0.031	0.032	0.049

Note: This table report the annualized CER gains and SR. The CER gains are calculated by the difference between the CER generated by tested model and the CER generated by benchmark model (i.e., HAR-RV). The tested models are HAR-RV-DS, HAR-RV-TS and HAR-RV-NS, respectively. NS, TS, and DS represent overnight sentiment, trading-hour sentiment and daily sentiment, respectively. SR is Shape ratio. *gamma* is relative risk aversion coefficient. The rolling window for out-of-sample forecasting is 200. The optimal weight is set between 0 and 1.

Table 9
In-sample regression results (highly volatile sample).

Variables	(1) RV_{t+1}	(2) RV_{t+1}	(3) RV_{t+1}	(4) RV_{t+1}
RV	0.281***	0.235***	0.247***	0.221***
	(3.70)	(3.16)	(3.30)	(3.09)
RVW	0.500***	0.388***	0.410***	0.353***
	(4.35)	(3.41)	(3.57)	(3.23)
RVM	0.043	0.005	0.012	0.006
	(0.38)	(0.04)	(0.11)	(0.06)
DS		−1.722***		
		(−4.39)		
TS			−1.786***	
			(−3.60)	
NS				−7.570***
				(−6.28)
Constant	0.866*	0.790	0.729	1.156**
	(1.68)	(1.59)	(1.45)	(2.40)
R-squared	0.427	0.469	0.456	0.506

Note: This table reports in-sample regression results of highly volatile sample. RV, RVW, and RVM is the daily, weekly and monthly realized volatility. NS, TS, and DS represent overnight sentiment, trading-hour sentiment and daily sentiment, respectively. The highly volatile sample is from January 2015 to January 2016. T-statistics are listed in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% level.

Table 10
Out-of-sample forecasting performance (highly volatile sample).

Tested model	Benchmark model	R^2_{os}(%)	CW	*p*-value
HAR-RV-DS	HAR-RV	15.302	1.952	0.025
HAR-RV-TS	HAR-RV	12.660	1.651	0.049
HAR-RV-NS	HAR-RV	17.553	2.659	0.004
HAR-RV-NS	HAR-RV-DS	2.656	1.883	0.029
HAR-RV-NS	HAR-RV-TS	5.602	2.043	0.020

Note: This table reports out-of-sample forecasting performance of highly volatile sample. NS, TS, and DS represent overnight sentiment, trading-hour sentiment and daily sentiment, respectively. The rolling window for out-of-sample forecasting is 200. The highly volatile sample is from January 2015 to January 2016.

Tables 9 and 10 report the results of in-sample regression and out-of-sample forecasting performance for this highly volatile subsample, respectively. Table 9 shows that the R^2 of HAR-RV model is 42.7% during highly volatile sample. When trading sentiment TS is added to the model, the R^2 is improved to 45.6%. In contrast, when overnight sentiment NS is added to the model, the R^2 increases to 50.6%. The larger increase of R^2 when including NS than TS suggests that, even during the period of high volatility, the effect of overnight sentiment on volatility remains greater than that of trading-hour sentiment, consistent with the conclusion using the full sample. Table 10 shows that the out-of-sample forecasting performance is improved when investor sentiment is included in the HAR-RV model during this highly volatile period. Importantly, the CW tests show that the forecasting performance of NS is better than that of TS and DS.

Table 11
In-sample regression results (pandemic period).

Variables	(1) RV_{t+1}	(2) RV_{t+1}	(3) RV_{t+1}	(4) RV_{t+1}
RV	0.318***	0.239***	0.264***	0.265***
	(7.31)	(5.50)	(6.02)	(6.37)
RVW	0.417***	0.442***	0.433***	0.432***
	(6.17)	(6.77)	(6.52)	(6.74)
RVM	−0.030	−0.066	−0.066	−0.039
	(−0.40)	(−0.92)	(−0.91)	(−0.56)
DS		−0.547***		
		(−7.34)		
TS			−0.593***	
			(−5.48)	
NS				−1.368***
				(−9.11)
Constant	0.219***	0.218***	0.191***	0.306***
	(4.40)	(4.54)	(3.90)	(6.34)
R-squared	0.333	0.379	0.360	0.401

Note: This table reports in-sample regression results of pandemic period. RV, RVW, and RVM is the daily, weekly and monthly realized volatility. NS, TS, and DS represent overnight sentiment, trading-hour sentiment and daily sentiment, respectively. The pandemic period is from January 2020 to December 2022. T-statistics are listed in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% level.

Table 12
Out-of-sample forecasting performance (pandemic period).

Tested model	Benchmark model	R^2_{os} (%)	CW	*p*-value
HAR-RV-DS	HAR-RV	4.131	1.952	0.025
HAR-RV-TS	HAR-RV	2.257	1.651	0.049
HAR-RV-NS	HAR-RV	8.913	2.660	0.004
HAR-RV-NS	HAR-RV-DS	4.987	1.884	0.030
HAR-RV-NS	HAR-RV-TS	6.810	2.043	0.021

Note: This table reports out-of-sample forecasting performance of pandemic period. NS, TS, and DS represent overnight sentiment, trading-hour sentiment and daily sentiment, respectively. The rolling window for out-of-sample forecasting is 200. The pandemic period is from January 2020 to December 2022.

5.2. Pandemic subsample

The COVID-19 epidemic had a significant impact on the global economy and the stock market. To examine the predictive power of investor sentiment during this period, we repeat our analyses with the subsample of the COVID period (January 1, 2020 to December 31, 2022). Tables 11 and 12 report the in-sample regression results and out-of-sample forecasting performance during the pandemic period. Table 11 shows that the R^2 of HAR-RV model drops to 33.3% during this period. The R^2 of HAR-RV-NS model increases to 40.1%. While the R^2 of the HAR-RV-TS model also increases, it is significantly less than that of the HAR-RV-NS model. Furthermore, the coefficient of TS (−0.593) is only 43% of the coefficient of NS (−1.368). This result is consistent with our earlier results that the predictive power of overnight sentiment is higher to trading-hour sentiment. The out-of-sample forecasting performance in Table 12 gives the same conclusion.

Table 13
Alternative rolling window size.

Tested model	Benchmark model	R^2_{os} (%)	CW	*p*-value
Panel A. Rolling window size: 100				
HAR-RV-DS	HAR-RV	13.953	2.130	0.017
HAR-RV-TS	HAR-RV	12.145	1.863	0.031
HAR-RV-NS	HAR-RV	15.678	2.831	0.002
HAR-RV-NS	HAR-RV-DS	2.005	2.321	0.010
HAR-RV-NS	HAR-RV-TS	4.022	2.395	0.008
Panel B. Rolling window size: 300				
HAR-RV-DS	HAR-RV	10.393	1.973	0.024
HAR-RV-TS	HAR-RV	8.927	1.687	0.046
HAR-RV-NS	HAR-RV	12.073	2.663	0.004
HAR-RV-NS	HAR-RV-DS	1.874	2.022	0.022
HAR-RV-NS	HAR-RV-TS	3.454	2.094	0.018
Panel C. Rolling window size: 500				
HAR-RV-DS	HAR-RV	10.247	1.971	0.024
HAR-RV-TS	HAR-RV	8.766	1.685	0.046
HAR-RV-NS	HAR-RV	12.016	2.668	0.004
HAR-RV-NS	HAR-RV-DS	1.971	2.065	0.019
HAR-RV-NS	HAR-RV-TS	3.563	2.123	0.017
Panel C. Rolling window size: 800				
HAR-RV-DS	HAR-RV	9.900	1.980	0.024
HAR-RV-TS	HAR-RV	8.562	1.692	0.045
HAR-RV-NS	HAR-RV	11.637	2.708	0.003
HAR-RV-NS	HAR-RV-DS	1.927	2.135	0.016
HAR-RV-NS	HAR-RV-TS	3.363	2.162	0.015

Note: This table reports out-of-sample forecasting performance using alternative rolling window size. NS, TS, and DS represent overnight sentiment, trading-hour sentiment and daily sentiment, respectively.

5.3. Alternative rolling window size

The choice of rolling window size may affect the evaluation of out-of-sample forecasting performance. As robustness check, we consider alternative rolling window sizes of 100, 300, 500, and 800. Table 13 reports the out-of-sample results of alternative rolling window sizes. The results show that all R^2_{os} are positive and statistically significant at 5% level or stronger. These results are consistent with Table 6. Therefore, the out-of-sample forecasting performance is robust to alternative rolling window size.

5.4. Alternative sentiment proxy

(1) Relative sentiment proxy

Following Antweiler and Frank (2004), we employ relative ratio to measure investor sentiment. Specifically, overnight sentiment, trading-hour sentiment and daily sentiment are redefined as follows

$$RDS_t = (PSent_t - NSent_t)/(PSent_t + NSent_t), \quad (20)$$

$$RTS_t = (TPSent_t - TNSent_t)/(TPSent_t + TNSent_t), \quad (21)$$

$$RNS_t = (NPSent_t - NNSent_t)/(NPSent_t + NNSent_t), \quad (22)$$

where RDS_t, RTS_t and RNS_t represent the daily sentiment, trading-hour sentiment and overnight sentiment measured by relative ratio respectively. PSent_t (NSent_t) is the sum of positive (negative) sentiment from 0:00 a.m. to 24:00 p.m. on day t. TPSent_t (TNSent_t) is the sum of positive (negative) sentiment from 9:30 a.m. to 15:00 p.m. on trading day t. NPSent_t (NNSent_t) is the sum of positive (negative) sentiment words from 15:00 p.m. on trading day t to 9:25 a.m. on trading day t + 1. Similar to the definition of overnight sentiment in Section 2.1, if day t + 1 is a weekend or holiday, the weekend and holiday's sentiments words are included in NPSent_t (NNSent_t).

Table 14
In-sample regression results using relative sentiment proxy.

Variables	(1) RV_{t+1}	(2) RV_{t+1}	(3) RV_{t+1}	(4) RV_{t+1}
RV	0.268***	0.262***	0.267***	0.261***
	(10.27)	(10.02)	(10.19)	(9.96)
RVW	0.492***	0.494***	0.491***	0.490***
	(12.31)	(12.37)	(12.26)	(12.29)
RVM	0.145***	0.137***	0.140***	0.136***
	(4.10)	(3.86)	(3.93)	(3.86)
RDS		−0.839**		
		(−2.48)		
RTS			−0.620*	
			(−1.83)	
RNS				−0.966***
				(−4.37)
Constant	0.118**	0.072	0.062	0.164***
	(2.43)	(1.38)	(1.06)	(3.29)

Note: This table reports using relative sentiment proxy. RV, RVW, and RVM is the daily, weekly and monthly realized volatility. RNS, RTS, and RDS represent relative overnight sentiment, trading-hour sentiment and daily sentiment, respectively. T-statistics are listed in parentheses. ***, ** and * indicate significance at the 1%, 5%, and 10% level.

Table 15
Out-of-sample forecasting performance using relative sentiment proxy (one-day-ahead).

Tested model	Benchmark model	R^2_{os}(%)	CW	*p*-value
HAR-RV-RDS	HAR-RV	−0.508	1.529	0.063
HAR-RV-RTS	HAR-RV	−0.464	0.913	0.181
HAR-RV-RNS	HAR-RV	1.387	2.536	0.006
HAR-RV-RNS	HAR-RV-RDS	1.885	2.603	0.005
HAR-RV-RNS	HAR-RV-RTS	1.842	2.619	0.004

Note: This table reports out-of-sample forecasting performance using relative sentiment proxy. RNS, RTS, and RDS represent relative overnight sentiment, trading-hour sentiment and daily sentiment, respectively. The rolling window for out-of-sample forecasting is 200.

Tables 14 and 15 show in-sample regression results and out-of-sample forecasting performance using relative sentiment ratios. Table 14 suggests that the effect of RNS_t on RV_{t+1} is significantly negative at level 1%. In contrast, the effect of RDS_t on RV_{t+1} is significant at 5% level, and the effect of RTS_t on RV_{t+1} is significant at 10% level. Table 15 shows that the out-of-sample prediction accuracy of HAR-RV-RNS is higher than that of other models. For example, the R^2_{os} in the case of HAR-RV-RNS versus HAR-RV is 1.387% and significant at 1% level, and the R^2_{os} in the case of HAR-RV-RNS versus HAR-RV-RTS is 1.842% and significant at 1% level. In conclusion, the results in Tables 14 and 15 confirm that overnight investor sentiment has richer information for predicting future volatility than daily sentiment and trading-hour sentiment.

(2) Orthogonalized sentiment proxy

Investor sentiment may be driven by information such as macroeconomic news. To control for rational component, we construct a new sentiment proxy (i.e., orthogonalized sentiment proxy) by orthogonalizing the sentiment proxy with industrial added value, consumer price index, producer price index, one-year deposit and loan interest rate, business index of macroeconomic, supply of money (M2), and deposit reserve ratio. Tables 16 and 17 show in-sample regression results and out-of-sample forecasting performance using orthogonalized sentiment proxy. Our results remain robust.

(3) Positive sentiment and negative sentiment

The sentiment extracted from Internet media may be positive or negative. It is unclear whether positive and negative sentiment affect returns in the expected direction, and whether they have similar impact on stock price volatility. To check the relationship between the two types of sentiment and stock returns, we

Table 16
In-sample regression results using orthogonalized sentiment proxy.

Variables	(1) RV_{t+1}	(2) RV_{t+1}	(3) RV_{t+1}	(4) RV_{t+1}
RV	0.268***	0.235***	0.243***	0.234***
	(10.27)	(8.60)	(8.84)	(8.74)
RVW	0.492***	0.466***	0.473***	0.451***
	(12.31)	(11.22)	(11.35)	(11.01)
RVM	0.145***	0.160***	0.156***	0.166***
	(4.10)	(4.36)	(4.24)	(4.59)
DS		−0.720***		
		(−7.00)		
TS			−0.725***	
			(−5.54)	
NS				−3.106***
				(−10.37)
Constant	0.118**	0.182***	0.168***	0.196***
	(2.43)	(3.44)	(3.16)	(3.76)
R-squared	0.542	0.553	0.549	0.566

Note: This table reports in-sample regression results using orthogonalized sentiment proxy. RV, RVW, and RVM is the daily, weekly and monthly realized volatility. NS, TS, and DS represent orthogonalized overnight sentiment, trading-hour sentiment and daily sentiment, respectively. T-statistics are listed in parentheses. ***, ** * indicate significance at the 1%, 5%, and 10% level.

Table 17
Out-of-sample forecasting performance using orthogonalized sentiment proxy (one-day-ahead).

Tested model	Benchmark model	R^2_{os} (%)	CW	*p*-value
HAR-RV-RDS	HAR-RV	10.906	2.000	0.023
HAR-RV-RTS	HAR-RV	9.447	1.759	0.039
HAR-RV-RNS	HAR-RV	13.259	2.706	0.003
HAR-RV-RNS	HAR-RV-RDS	2.640	1.994	0.023
HAR-RV-RNS	HAR-RV-RTS	4.209	2.108	0.018

Note: This table reports out-of-sample forecasting performance using orthogonalized sentiment proxy. NS, TS, and DS represent orthogonalized overnight sentiment, trading-hour sentiment and daily sentiment, respectively. The rolling window for out-of-sample forecasting is 200.

separate positive and negative sentiment and regress them with contemporaneous returns. Table 18 reports the regression results. The table shows that positive sentiment is significantly positively correlated with returns on the same day, while negative sentiment is significantly negatively correlated with returns on the same day. The results are line with behavioral finance theory, which indicates positive (negative) sentiment drives up (down) prices in the short term.

To assess the relative importance of two types of sentiment on volatility forecasting, we add positive and negative investor sentiment to the HAR-RV model respectively and test its predictive performance. By doing so, we try to answer (1) whether both sentiments can predict realized volatility; (2) which one is more informative to forecast volatility; and (3) whether overnight positive or negative sentiment is still superior to that in trading-hours in volatility forecasting. First, we use HAR-RV as the benchmark model to test the independent predictive performance of positive or negative sentiment. The results in Table 19 (row 1–4) show that individual positive or negative sentiment can also improve predictive performance. Second, we compare the differences in predictive power between positive and negative sentiment during the same period. The results in Table 19 (row 5–6) indicate that the predictive ability of negative sentiment is stronger than that of positive sentiment. Third, we test the difference between overnight positive (negative) sentiment and trading-hour positive (negative) sentiment. The results in Table 19 (row 7–8) indicate that the predictive ability of overnight positive (negative) sentiment is stronger than trading-hour positive (negative) sentiment.

Table 18
The relation between positive (negative) sentiment and contemporaneous returns.

Variables	(1) Ret	(2) Ret	(3) Ret
DPS	0.024***		
	(24.39)		
DNS	−0.020***		
	(−33.11)		
TPS		0.030***	
		(20.33)	
TNS		−0.024***	
		(−28.08)	
NPS			0.049***
			(27.42)
NNS			−0.052***
			(−37.34)
Constant	0.001***	0.002***	0.002***
	(3.17)	(5.15)	(5.62)
R-squared	0.396	0.335	0.427

Note: This table report the relation between positive (negative) sentiment and contemporaneous returns. DPS, NPS and TPS represent positive daily sentiment, positive overnight sentiment and positive trading-hour sentiment. DNS, NNS and TNS represent negative daily sentiment, negative overnight sentiment and negative trading-hour sentiment. Ret is the returns of the Shanghai Composite Index.

Table 19
Out-of-sample forecasting performance comparison of positive and negative sentiment.

	Tested model	Benchmark model	R^2_{os} (%)	CW	*p*-value
(1)	HAR-RV-TPS	HAR-RV	8.094	1.673	0.047
(2)	HAR-RV-NPS	HAR-RV	14.214	2.374	0.009
(3)	HAR-RV-TNS	HAR-RV	9.277	1.700	0.045
(4)	HAR-RV-NNS	HAR-RV	17.818	2.686	0.004
(5)	HAR-RV-TNS	HAR-RV-TPS	1.287	1.303	0.096
(6)	HAR-RV-NNS	HAR-RV-NPS	4.201	2.060	0.020
(7)	HAR-RV-NPS	HAR-RV-TPS	6.658	2.345	0.009
(8)	HAR-RV-NNS	HAR-RV-TNS	9.414	2.612	0.004

Note: This table report out-of-sample forecasting performance comparison of positive and negative sentiment. NPS and TPS represent positive overnight sentiment and positive trading-hour sentiment. NNS and TNS represent negative overnight sentiment and negative trading-hour sentiment. The rolling window for out-of-sample forecasting is 200.

5.5. Overnight sentiment vs overnight returns

As mentioned earlier, the existing literature measures overnight information by overnight returns (Ahoniemi and Lanne, 2013; Wang et al., 2015; Liang et al., 2021). For example, Aboody et al. (2018) use overnight returns as a proxy for investor sentiment. Prapan and Vagenas-Nanos (2022) use absolute overnight returns as a proxy of investor attention. Wang et al. (2015) use negative overnight returns to represent leverage effects and show that they play a significant role on volatility forecasting. Some studies show that the predictive power of investor sentiment on volatility is negligible after controlling for the leverage effect (Wang et al., 2006; Yang et al., 2019; Gong et al., 2022). To test the influence of overnight returns on the predictive power of overnight sentiment for volatility, we construct HAR-RV model with overnight returns:

$$OR_t = \ln OP_t - \ln CP_{t-1}, \tag{23}$$

$$ORS_t = |OR_t|\,, \tag{24}$$

$$Lev_t = \min(OR_t, 0), \tag{25}$$

where OR_t is overnight returns (investor sentiment proxy), ORS_t is absolute overnight returns (investor attention proxy), and Lev_t

Table 20
In-sample regression results including overnight returns.

Variables	(1) RV_{t+1}	(2) RV_{t+1}	(3) RV_{t+1}	(4) RV_{t+1}	(5) RV_{t+1}	(6) RV_{t+1}
RV	0.262***	0.260***	0.258***	0.232***	0.230***	0.231***
	(10.08)	(10.04)	(9.99)	(9.11)	(9.02)	(9.06)
RVW	0.492***	0.447***	0.466***	0.454***	0.420***	0.439***
	(12.38)	(11.11)	(11.75)	(11.65)	(10.68)	(11.28)
RVM	0.133***	0.138***	0.131***	0.127***	0.128***	0.124***
	(3.77)	(3.95)	(3.75)	(3.68)	(3.73)	(3.63)
OR	−0.359***			−0.183***		
	(−5.70)			(−2.87)		
ORS		0.526***			0.397***	
		(6.50)			(4.96)	
Lev			−0.586***			−0.375***
			(−7.10)			(−4.48)
NS				−2.820***	−2.830***	−2.716***
				(−10.02)	(−10.37)	(−9.72)
Constant	0.107**	0.011	0.050	0.195***	0.120**	0.154***
	(2.22)	(0.22)	(1.01)	(4.06)	(2.36)	(3.12)
R-squared	0.549	0.551	0.553	0.570	0.573	0.572

Note: This table reports in-sample regression results including overnight returns. NS, TS, and DS represent overnight sentiment, trading-hour sentiment and daily sentiment, respectively. OR is overnight returns, ORS is absolute overnight returns, and Lev is negative overnight returns. RV, RVW, and RVM is the daily, weekly and monthly realized volatility.

Table 21
Out-of-sample forecasting performance comparison of overnight returns and overnight sentiment.

Tested model	Benchmark model	R^2_{os} (%)	CW	*p*-value
HAR-RV-NS	HAR-RV-OR	8.724	2.614	0.004
HAR-RV-NS	HAR-RV-ORS	7.136	2.749	0.003
HAR-RV-NS	HAR-RV-Lev	7.140	2.690	0.004

Note: This table report out-of-sample forecasting performance comparison of overnight returns and overnight sentiment. NS is overnight sentiment. OR is overnight returns, ORS is absolute overnight returns, and Lev is negative overnight returns, which represent leverage effect.

represent leverage effect. CP_{t-1} is closing price on day t + 1, and OP_t is opening price on day t.

Table 20 lists the in-sample regression results. Table 20 shows that overnight returns, absolute overnight returns, and negative overnight returns do affect future volatility. OR_t and Lev_t are significantly negatively correlated with volatility. ORS_t is significantly positively correlated with future volatility. In terms of goodness-of-fit, the increase of R^2 is very limited when OR_t, Lev_t, and ORS_t are included in the HAR-RV model compared with the benchmark HAR-RV model (see Table 6). More importantly, when three measures of overnight returns are included in the HAR-RV model, the overnight sentiment remains significantly negative at 1% level. This result indicates that the predictive power of overnight sentiment is not driven by overnight returns.

Table 21 lists the out-of-sample forecasting performance comparison of overnight returns and overnight sentiment. The HAR-RV-NS is selected as tested model. The HAR-RV-OR, HAR-RV-ORS and HAR-RV-Lev are used as benchmark model. Table 21 shows the R^2_{os} are all positive and significant at 1% level. The last three rows of Table 7 report the results of MCS testing. Taken together, these results indicate that overnight sentiment has more information than overnight returns when predicting volatility.

6. Conclusion

With the help of Chinese sentiment dictionary, we extract investor sentiment from internet social forums. We further decompose daily sentiment into overnight sentiment and trading-hour sentiment. Our empirical analyses suggest that investor sentiment significantly affects realized volatility. More importantly, we find that overnight sentiment has significantly greater predictive power on volatility than trading-hour sentiment and daily sentiment. Our results hold in different subsamples, and are robust to alternative rolling window sizes and sentiment proxies. We further show that the predictive power of overnight sentiment is not affected by the inclusion of overnight returns.

This research is important to academics and market investors for two reasons. First, the inclusion of overnight sentiment in the HAR-RV model can significantly improve the prediction accuracy. This has important implications for investors who use Chinese A-shares in their portfolio hedging and trading strategies. Second, our findings are important for a better understanding of the source of the predictive power of sentiment. Our results suggest that overnight sentiment contain novel information, while trading-hour investor sentiment is more affected by trading prices, and the source of the predictive power of sentiment may come from information.

CRediT authorship contribution statement

Xiaojun Chu: Conceptualization, Methodology, Formal analysis, Writing. **Xinmin Wan:** Empirical data analysis, Revision. **Jianying Qiu:** Review & editing.

Declaration of competing interest

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

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Appendix A. Supplementary data

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