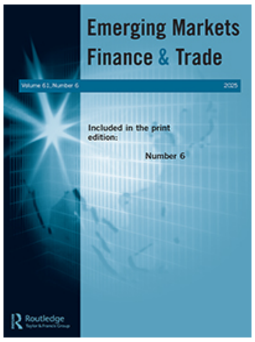

Emerging Markets Finance and Trade

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/mree20

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EMERGING MARKETS FINANCE AND TRADE
https://doi.org/10.1080/1540496X.2025.2474720

A News Sentiment Index and Its Asymmetric Effect on Market Liquidity for the Chinese Stock Market

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ABSTRACT
This paper measured investor sentiment using the News Sentiment Index (NSI) and examined its asymmetric impact on market liquidity, particularly focusing on how these effects changed during the COVID-19 pandemic in the Chinese stock market. Constructed from comprehensive news data sourced from the Global Database on Events, Location, and Tone (GDELT), the NSI encapsulates the sentiment dynamics relevant to the Chinese stock market. We applied the unit root and cointegration tests with time-varying volatilities, which showed that sentiment follows a random walk with time-varying volatility and is cointegrated (co-moved) with liquidity. While the relationship between sentiment and market liquidity has been extensively studied, the asymmetric effects of sentiment on liquidity have remained largely unexplored. Our study fills this gap by applying the vector error correction model (VECM), which revealed that liquidity's response to sentiment is more pronounced under pessimistic conditions (7.04%) compared to optimistic ones (6.13%). However, this asymmetry appears to have been moderated during the COVID-19 pandemic, indicating a shift in sentiment's influence on liquidity amid heightened uncertainty. By capturing the dynamics of investor sentiment and its asymmetric effects under different market conditions, this study deepens our understanding of investor sentiment and its relationship with liquidity.

KEYWORDS
News sentiment; random walk with time-varying volatility; co-movement; market liquidity; asymmetric effect

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G10; G14

Introduction

Investor sentiment is a pivotal concept within financial economics, extensively discussed and variously measured (Baker and Wurgler 2006; Da, Engelberg, and Gao 2015; Gong et al. 2022; Kostopoulos, Meyer, and Uhr 2020; Wang, Su, and Duxbury 2021). How to accurately quantify this sentiment, however, still remains a contentious issue that has sparked considerable debate within the field. In light of this, our study developed the News Sentiment Index (NSI) tailored for the Chinese stock market, which attempts to enhance the precision of the existing sentiment measurement. To shed more lights to the dynamics of investor sentiment, we further explored the relationships between sentiment and liquidity. While the effects of investor sentiment on stock market dynamics, including market liquidity, have been extensively documented (Ammari, Chebbi, and Ben Arfa 2023; Debata, Dash, and Mahakud 2018; Liu 2015; Liu, Wu, and Zhou 2023; Yin, Wu, and Kong 2022), the asymmetry of the sentiment's impact on liquidity has been largely overlooked. Yet, we try to address this gap.

The Chinese equity market, as the world's second-largest stock exchange, trailing only the US. It exhibits distinct characteristics that differentiate it from the stock markets of developed countries. First, restrictions on short selling make it more susceptible to sentiment-driven effects (Lin and Qiu 2023), while the dominance of individual investors—accounting for 85% of daily trading volume

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(Jones et al. 2025)—leads to greater sensitivity to news. Second, the Chinese market's growing openness, facilitated by mechanisms such as QFII (Qualified Foreign Institutional Investor) and RQFII (RMB Qualified Foreign Institutional Investor) (Zhang et al. 2023), has made it an important avenue for foreign investment, further linking it to global sentiment flows.[1] This growing international exposure not only allows foreign investors to diversify their portfolios through the Chinese stock market but also makes the market more vulnerable to the influence of international information. Consequently, the unique structure of the Chinese equity market, with its increased susceptibility to rumors, speculation, and herding behaviors, renders it an ideal environment for sentiment analysis.

Against this backdrop, we constructed a sentiment index specifically for the Chinese stock market by applying natural language processing (NLP) technologies on the extracted relevant news data concerning China from the Global Database on Events, Location, and Tone (GDELT). This indicator could capture investors' real-time reactions to economic, political, and financial events, which renders it to effectively mirror the dynamic nature of the Chinese stock market, thus providing a robust measure for sentiment analysis.

Though fruitful results have been yielded, the debate continues over whether sentiment indicators should inherently reflect certain characteristics prevalent in investors' psychological activities, such as time-varying volatility and non-stationarity (Fang et al. 2020; Long, Zhao, and Tang 2021). Specifically, investor sentiment, which mirrors future expectations based on the flow of available information (Baker and Wurgler 2006), is naturally expected to exhibit randomness due to the sporadic and unpredictable nature of information dissemination. Secondly, it's plausible that time-varying volatility is a fundamental attribute of investor sentiment, arising from the influence of economic shocks and ongoing information flows. Crucially, the accurate identification of whether our sentiment index follows a random walk is essential, as misidentification of random walk data as stationary can lead to inconsistent model estimations and invalid statistical inferences. Furthermore, time-varying volatility challenges the reliability of standard unit root tests, such as the ADF and MZ tests (Cavaliere and Taylor 2008, 2009). To address these concerns, we used the wild bootstrap ADF and MZ tests developed by Cavaliere and Taylor (2008, 2009), which are specifically designed to accommodate such volatilities. Our results corroborate the hypothesis that the NSI follows a random walk process with time-varying volatility, a critical aspect that has been largely overlooked in prior research.

To shed more light on the sentiment dynamics, we extensively delved into the relationship between sentiment and liquidity. Specifically, we adopted Turnover Rate (TR) as the proxy for liquidity, as supported by established literature (Brown, Crocker, and Foerster 2009; Chordia, Subrahmanyam, and Anshuman 2001; Levine and Schmukler 2006; Nguyen et al. 2007; Rouwenhorst 1999). Subsequently, we investigated the long-term relationship between NSI and TR through a cointegration model. The cointegration results demonstrated a sustained connection between sentiment and liquidity.

To gain more insights on this relationship, we employed the asymmetric vector error correction model (VECM). The findings indicated that the optimistic and pessimistic sentiment affects liquidity asymmetrically. Notably, we observed that this asymmetry diminished during the COVID-19 pandemic, which suggested that major disease outbreaks may significantly influence investor sentiment (Donadelli, Kizys, and Riedel 2017; Sun, Bao, and Lu 2021). What should be highlighted is that the impact of the COVID-19 pandemic on China was notably severe and differed markedly from typical economic crises. First, China's strict containment measures led to immediate and extensive disruptions in economic production, far exceeding the impact of conventional crises. Second, the pandemic shifted decision-making reliance from traditional financial data to media reports, reflecting the unique challenges of managing a health crisis (Bai et al. 2023). Despite these, research on the COVID-19 pandemic's specific impact on Chinese investor sentiment remains limited (Sun, Bao, and Lu 2021). However, our analysis of the NSI's impact on TR supplemented this field and indicated that during the pandemic there was a reduction in the asymmetry of sentiment's impacts on liquidity. This was likely due to an optimism bias driven by strong government interventions, which amplified the market's sensitivity to positive news sentiment. This shift suggested that the pandemic reshaped the traditional dynamics of how sentiment influences liquidity, warranting further investigation into these effects.

This study contributes to the literature in three key ways. Firstly, this study developed a news sentiment index based on the global textual news database, which mirrors the dynamics of the Chinese stock market more effectively than existing methodologies. Notably, we found that the NSI follows a random walk process with time-varying volatility, shedding new light to Chinese stock market dynamics. Second, our findings indicated that the NSI co-moves with the TR, suggesting a long-term equilibrium relationship between market sentiment and liquidity. Third, we observed that sentiment affects liquidity asymmetrically, with the degree of this asymmetry diminishing during the COVID-19 pandemic. This shift offers insights into how global health crisis can reshape established behavioral patterns of sentiment and liquidity.

The remainder of this paper is organized as follows. Section "Literature Review" provides an overview of the related literature. Section "News Sentiment Index and Turnover Rate" describes constructing of NSI and the reason why we use turnover rate to proxy the market liquidity. Section "Methodology" shows the methodology used in this paper. Section "Empirical Results" presents the main empirical results. Section "Conclusions" presents the conclusions.

Literature Review

Measurement Approaches for Investor Sentiment

The measurement of investor sentiment in existing literature can be divided into three strands. The initial phase is survey-based, which employed survey data to formulate market sentiment indices. The well-known instances include the American Association of Individual Investors Index, the Investors' Intelligence Index, and the Consumer Confidence Index. However, these indices are fraught with various limitations, including high cost, availability latency, non-replication difficulty, lack of incentives for honest responses, and inability to be backtested (Fabozzi and Nazemi 2023).

Another strand has endeavored to leverage financial market variables such as trading volume, extreme one-day returns, and implied volatility to construct or serve as proxies for sentiment indices (Baker and Wurgler 2006; Gong et al. 2022; Huang et al. 2015). Foremost among these is the sentiment index proposed by Baker and Wurgler (2006) (Baker-Wurgler index, hereafter BW index), wherein they utilized the first principal component of six market variables, encompassing closed-end fund discount and turnover rate, to proxy the sentiment index. However, this approach may not universally apply across all markets. They also faced criticism that the movements of these proxies may also be partially driven by fundamentals (Da, Engelberg, and Gao 2015).

There is a growing body of literature showing that sentiment measures based on text analysis-based approach outperforms the aforementioned measures (Zhou 2018). Therefore, researchers began to embrace text mining techniques. Text-based methodologies draw upon extensive textual data from sources such as online message posts, newspapers, and search engine search volumes to construct sentiment index. Lexicon-based or machine-learning techniques were employed to craft sentiment indices (Da, Engelberg, and Gao 2015; De Freitas Rocha Cambara and Meurer 2023; Gu and Kurov 2020; Tetlock 2007; Xu et al. 2023). The advantage of text-based indices lies in their ability to capture real-time sentiment from a wide variety of sources, providing a more dynamic and responsive measure compared to traditional market-based or survey-based indices. For instance, Tetlock (2007) extracted sentiment indices from the Wall Street Journal reports using the Harvard IV-4 psychological dictionary. Gu and Kurov (2020) devised the Twitter index based on firm-specific Twitter news. Xu et al. (2023) constructed the monthly sentiment indices using information from social media, traditional newspapers, and Internet news. To sum up, in recent years, text-based methods have garnered increased favor due to rapid advancements in data collection and natural language processing technologies.

Impact of Investor Sentiment on Stock Market

In the literature, the relationship between investor sentiment and some directly observable variable, such as market liquidity, has garnered considerable attention. In particular, with the rise of extensive research on investor sentiment, its influence on liquidity has also been widely studied (Ammari, Chebbi, and Ben Arfa 2023; Debata, Dash, and Mahakud 2018; Liu 2015; Liu, Wu, and Zhou 2023; Yin, Wu, and Kong 2022). The theoretical foundations of the influence of this relationship include noise traders, irrational market makers, and overconfidence theories. An array of studies attested that investor sentiment instigates fluctuations in liquidity. For instance, Liu (2015) asserted that positive (negative) investor sentiment increases (decreases) market liquidity. Debata, Dash, and Mahakud (2018) found a positive (negative) effect of investor sentiment on liquidity (illiquidity) in emerging markets. Yin, Wu, and Kong (2022) unveiled a positive correlation between investor sentiment and stock liquidity.

Additionally, recent literature has extensively delved into the asymmetric effects of investor sentiment on the stock market dynamic (Chau, Deesomsak, and Koutmos 2016; Chen, Chen, and Lee 2013; Dahmene, Boughrara, and Slim 2021; Wang, Su, and Duxbury 2022; Yu and Yuan 2011). Yu and Yuan (2011) found that the stock market's expected excess return is positively related to the market's conditional variance in low-sentiment periods but unrelated to variance in high-sentiment periods. Chau, Deesomsak, and Koutmos (2016) suggested that in the U.S. market, bearish sentiment-driven trading behaviors are more prone. Wang, Su, and Duxbury (2022) proposed that in bull markets, optimistic (pessimistic) shifts in investor sentiment would increase (decrease) stock returns, while in bear markets, optimistic (pessimistic) shifts would decrease (increase) stock returns. However, the quantitative analysis of the symmetric effects of sentiment on liquidity remains limited, a gap that this study aims to address.

Overall, our study focuses on the dynamic evolution of sentiment and its asymmetric effect on liquidity, which may capture the unique characteristics of the Chinese stock market and contribute to the existing literature.

News Sentiment Index and Turnover Rate

The Global Database of Events, Language, and Tone

The GDELT is an open-access database that collects global online news every 15 minutes.[2] It stands out as an exceptional resource for constructing a sentiment index especially for China due to several key advantages. First, GDELT provides open access to its data, providing unrestricted data availability, making it convenient for researchers to validate and extend studies. Second, GDELT collects news sources from all over the world in over 100 languages, allowing for comprehensive analysis of over 2,300 emotions and themes. This feature is particularly beneficial for tracking the Chinese stock market, given its openness and links to global financial systems. International news, often in languages other than Chinese, can rapidly impact sentiment of investors in the Chinese stock market. Third, GDELT offers near real-time updates, ensuring that sentiment index captures rapid sentiment shifts and their effects on the stock market. This is especially valuable given the high responsiveness of retail investors in China to news, underscoring GDELT's role in providing timely, multilingual sentiment analysis. Therefore, GDELT's ability to provide real-time, multilingual sentiment analysis is particularly beneficial, enhancing the responsiveness and relevance of sentiment indices tailored to the dynamics of the Chinese stock market.

The Construction of the NSI for the Chinese Stock Market

Using GDELT, we have constructed a news sentiment index for the Chinese stock market. GDELT first extracts data from diverse sources including newspapers, blogs, podcasts, and videos in over 100 languages. In particular, non-English articles would be translated into English with GDELT

Translingual, which enhances the uniformity of the data for analysis. Subsequently, these data will be analyzed with NLP techniques by this database. During this analysis, key themes, people, and locations are identified and systematically categorized in corresponding fields.

Taking data availability into account, we selected the sample period from January 1, 2016, to December 31, 2022, when China ended its strict epidemic control policy. We applied specific filters on the pre-processed results from the GDELT database to isolate news related to the Chinese stock market. Our first filtering step focused on the "Theme" column. After reviewing all significant themes in the GDELT labeling system, we selected three themes, namely "ECON_STOCKMARKET" (discussions about any stock market or government bonds), "ECON_IPO" (Initial Public Offerings), and "ECON_BUBBLE" (discussions regarding economic and financial bubbles). These themes are directly linked to key drivers of stock market behavior, such as market performance, IPO activities, and concerns over market bubbles.[3] In our second filtering step, we refined the selection based on the "Location" column, only including reports that mentioned "China". This ensures that our analysis remained focused on news with direct relevance to the Chinese stock market.[4]

To assess sentiment, GDELT employs multiple sentiment dictionaries to ascertain the emotional classification (positive, negative, or neutral) of each word or phrase in every news article. The tone score of news article j, $Tone_j$, is defined as the difference of positive and negative words divided by the total word count in the text:

$$Tone_j = 100 * \frac{(\Sigma Positivewords - \Sigma Negativewords)}{\Sigma Totalwords} \tag{1}$$

This tone score for each article ranges from −100 (extremely negative) to +100 (extremely positive), though most scores fell between −10 and +10. And 0 indicates neutrality. Using the $Tone_j$, we constructed the news sentiment index for day t (denoted by NSI_t):

$$NSI_t = \frac{1}{M_t} \sum_{j=1}^{M_t} Tone_j \tag{2}$$

where M_t is the number of articles selected on day t, and NSI_t is the news sentiment index on day t. Similarly, $NSI_t \geq 0$ means that the news sentiment has a positive tone, whereas $NSI_t < 0$ means a negative tone. To offer more intuition, we plotted the NSI in Figure 1.

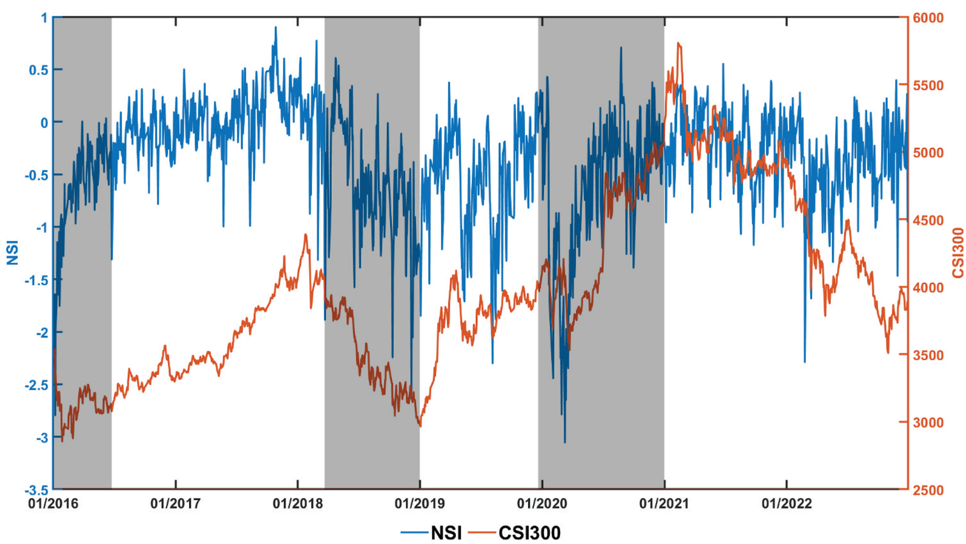

Figure 1. NSI and CSI 300 index date series and typical facts. The three shaded areas represent three typical facts: the stock market bubble recovery period, the Sino-US trade conflict, and the COVID-19 epidemic.

NSI: Capturing Investor Psychology and Typical Facts of the Chinese Stock Market

In this subsection, we shall demonstrate how the NSI effectively reflects well-known shifts in investor sentiment during key events in the Chinese stock market. Figure 1 shows the NSI and a Chinese stock market index (CSI 300 Index). The three shaded areas highlight major events: the recovery from the 2015 stock market disaster, the Sino-US trade conflict, and the COVID-19 pandemic.

First, the Chinese stock market experienced a significant bubble between 2015 and 2016 (Li, Wang, and Zhao 2020), with the bubble bursting on June 19, 2015, when the CSI 300 index hit 4637.052. The market then entered a recovery period until June 24, 2016, during which both the NSI and CSI 300 gradually rebounded from their lows. Notably, the NSI turned from negative to positive near the end of the recovery. This turning point indicates an improvement in investor sentiment as the market recovers.

Second, during the onset of the Sino-US trade conflict in March 2018, both the NSI and the CSI 300 exhibited a prolonged downward trend. The trade conflict, which disrupted global supply chains particularly in high-tech sectors, has led to widespread investor pessimism. This decline in investor sentiment, as reflected by the NSI, highlights the market's growing uncertainty and fear of prolonged economic downturns. The continuous drop in the NSI aligns closely with the intensification of trade tensions, as tariffs and restrictions between the two largest economies heightened concerns about global economic instability. The sustained downward trend of the NSI during this period reflects not only the immediate negative reaction to trade news but also the market's long-term anxiety about the potential ripple effects on global trade and technological development.

Finally, as the COVID-19 pandemic spread in December 2019, most factories and production activities were halted, and trade volume sharply declined. Investor sentiment gradually froze, with the NSI dropping below zero. The CSI 300 also reached a nadir during this period, aligning closely with the NSI's sentiment indicator. In sum, the above events and their alignment with NSI data provide strong evidence that the NSI accurately captured the market's response to the listed major events.

To further demonstrate the superiority of our newly constructed NSI, we conducted a comparative analysis with the leading sentiment indices within the Chinese stock market. Specifically, we compared the NSI with the BW sentiment indices from the China Stock Market & Accounting Research Database (CSMAR), namely the ISI (Investor Sentiment Index) and CICSI (Chinese Investor Composite Sentiment Index). These indices serve as standard benchmarks for monitoring investor sentiment and are extensively used to track market trends in China. The results, displayed in Figure 2, reveal distinct patterns in sentiment behavior between our NSI and the BW indices during the COVID-19 pandemic. Notably, the NSI shows a sharp decline, aligning more closely with the actual market conditions and economic downturns observed during the pandemic. In contrast, both ISI and CICSI show a rising trend, which appears counterintuitive given the economic disruptions at the time. This divergence highlights the NSI's enhanced sensitivity and reliability in capturing the true market sentiment.

To further substantiate our findings, we conducted a correlation analysis, as shown in Table 1. The results indicate a moderate correlation between our NSI and the BW indices, suggesting an alignment between the three indices prior to the pandemic. However, the distinct evolution of these indices during critical events such as COVID-19 pandemic make the NSI a more sensitive and accurate measure of market sentiment during such times. Therefore, we conclude that the NSI better represents investor sentiment in the Chinese market, especially in response to the pandemic.

Additionally, the alignment of NSI with CSI300 further demonstrates its effectiveness in mirroring stock market dynamics, reinforcing the NSI's role as a superior measurement of Chinese market sentiment. The comparison with traditional BW indices also highlights NSI's superior accuracy in capturing subtleties of Chinese market sentiment. With all these ideas in minds, the NSI proves to be a reliable proxy for investor sentiment in China.

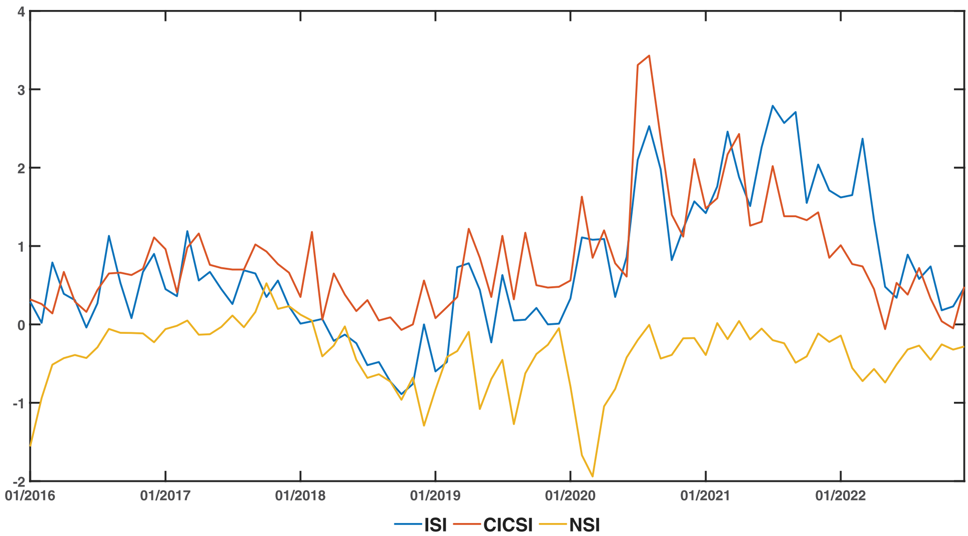

Figure 2. The time series of NSI, ISI, and CICSI.

Table 1. Correlation of NSI with ISI and CICSI.

Sentiment index	ISI	CICSI
Correlation with NSI	0.189*	0.232**
p-value	0.0851	0.0334

Notes. The correlation coefficients presented in this table are Pearson correlation coefficients. The statistical significance of the correlations was assessed using two-tailed hypothesis testing. Coefficients with a significance level less than 0.1 are denoted by one asterisk (*), and those with a significance level less than 0.05 are denoted by two asterisks (**).

Turnover Rate

In this study, we employed the turnover rate as a proxy for market liquidity, consistent with prior research such as Rouwenhorst (1999), Chordia, Subrahmanyam, and Anshuman (2001), Levine and Schmukler (2006), Nguyen et al. (2007), and Brown, Crocker, and Foerster (2009). The turnover rate effectively captures trading frequency, which is a key indicator of market liquidity (Easley and O'hara 1992; Engle and Russell 1998). By considering both trading volume and the market capitalization of stocks, TR provides a comprehensive measure of liquidity. Therefore, we adopted TR to investigate the relationship between investor sentiment and market liquidity.

Methodology

Time-Varying Volatility and Unit Root Tests

To examine the presence of time-varying volatility in our variables, we firstly applied the variance profile approach proposed by Cavaliere and Taylor (2007). Specifically, the variance profile, $\eta(s)$, is defined as follows:

$$\eta(s) := \left(\int_0^1 \omega(r)^2 dr\right)^{-1} \int_0^s \omega(r)^2 dr \tag{3}$$

where $\eta(s) = s$ under homoscedastic conditions. A consistent estimator of $\eta(s)$ is:

$$\hat{\eta}(s) = \frac{\sum_{t=1}^{\lfloor sT \rfloor} \Delta\hat{y}_t^2 + (sT - \lfloor sT \rfloor)\Delta\hat{y}_{\lfloor sT \rfloor+1}^2}{\sum_{t=1}^{T} \Delta\hat{y}_t^2} \tag{4}$$

where $s \in [0,1]$. $\Delta\hat{y}_t$ denotes the first-order difference of detrended y_t by the generalized least squares method, and $\lfloor x \rfloor$ denotes the greatest integer less than or equal to x. A deviation of $\hat{\eta}(s)$ from the straight line $\eta(s) = s$ suggests the presence of time-varying variance.

Considering the potential time-varying volatility, we employed wild bootstrap unit root tests to accommodate such variance as recommended by (Cavaliere and Taylor 2008, 2009). As they elaborated, the wild bootstrap method can replicate the dynamic evolving structure of the original data into the resampled bootstrap samples, thereby ensuring precise test critical values. In particular, the variables can be formulated as follows:

$$\Delta y_t = \alpha y_{t-1} + \sum_{i=1}^{p} \beta_i \Delta y_{\{t-i\}} + u_t \tag{5}$$

Here, $u_t = \sigma_t \varepsilon_t$ with $\varepsilon_t i.i.d.N(0,1)$, and σ_t can evolve over time, which is denoted as $\sigma_{[sT]} = w(s)$, for all $s \in [0,1]$. The null hypothesis of random walk, $H_0 : \alpha = 0$, was tested against the alternative hypothesis of stationarity, $H_1 : \alpha < 0$.

Under the wild bootstrap framework, the ADF and MZ statistics under the null hypothesis are defined as:

$$ADF_\tau = \frac{\hat{\alpha}}{se(\hat{\alpha})} \tag{6}$$

$$MZ_\tau = \frac{T^{-1}\hat{y}_T^2 - s_{AR}^2(p)}{2T^{-2}\sum_{t=2}^{T} \hat{y}_{t-1}^2} \times \left(T^{-2} \sum_{t=2}^{T} \hat{y}_{t-1}^2 / s_{AR}^2(p) \right)^{1/2} \tag{7}$$

where $\hat{y}_t$ denotes detrended y_t by the generalized least squares method. The terms $\hat{\alpha}$ and se$(\hat{\alpha})$ are the OLS estimator of α in Equation (5) and its standard error, respectively. The variance term $s_{AR}^2(p)$ is defined as: $s_{AR}^2(p) := \hat{\sigma}^2 / \left(1 - \hat{\beta}_p(1)\right)^2$, with $\hat{\beta}_p(1) := \sum_{i=1}^{p} \hat{\beta}_i$. Notably, Cavaliere and Taylor (2008, 2009) demonstrated that the limit distributions of both statistics are nonpivotal, depending on the nuisance parameters $\eta(s)$ under the time-varying volatility, as shown in Equations (6) and (7). The tabulated critical values, therefore, become invalid under these conditions. Thus, Cavaliere and Taylor (2008, 2009) proposed to compute the ADF and MZ statistics using wild bootstrap samples which can preserve the time-varying volatility structure inherent in the original data. Moreover, the asymptotic validity of the wild bootstrap ADF and MZ statistics has been established by Cavaliere and Taylor (2008, 2009). As a result, the wild bootstrap results we used are both accurate and reliable.

Cointegration Tests Under Time-Varying Volatility

We applied the wild bootstrap Engel-Granger two-step (EG2) cointegration test method to investigate the relationship between the NSI and TR, specifically within the context of time-varying volatility. Traditional approach employed in sentiment analysis usually involves using first-differencing to handle non-stationarity in sentiment index. However, as shown by Plosser and Schwert (1978) and Ardeni (1989), this method may not be optimal, potentially obscuring deeper, underlying relationships between variables. The wild bootstrap EG2 cointegration approach is particularly valuable in this context. According to Engle and Granger (1987), cointegration test offers a robust alternative to first-differencing by directly addressing the long-term equilibrium relationship between series without losing information about their dynamic interactions. Moreover, the wild bootstrap version by Wang, Zhao, and Li (2019) proved to be especially effective under conditions of time-varying volatility, where traditional EG2 cointegration test approach might fail to capture the nuances of the evolving market dynamics.

In our case, we could model the relationship between TR and NSI as follows:

$$TR_t = \alpha + \beta NSI_t + u_t \tag{8}$$

$$u_t = \rho u_{t-1} + v_t \tag{9}$$

Here, $v_t = \sigma_t \varepsilon_t$ with $\varepsilon_t i.i.d.N(0,1)$, and the volatility term σ_t may evolve over time as $\sigma_{[sT]} = w(s)$ for all $s \in [0,1]$. The null hypothesis for testing cointegration between NSI and TR posits that: $H_0 : \rho = 0$, impliying that there is no cointegration relationship, whereas the alternative hypothesis, $H_1 : \rho < 0$, implies a cointegration relationship, indicating a genuine long-term equilibrium relationship between these variables.

Wang, Zhao, and Li (2019) proposed the Z_t test statistic to test the null against alternative hypotheses as follows:

$$Z_t := \frac{T(\hat{\rho}-1)}{s_{TI}\left(T^{-2}\sum_{t=2}^{T}\hat{u}_{t-1}^2\right)^{-\frac{1}{2}}} - \frac{1}{2}\frac{s_{TI}^2(p)-s_v^2}{s_{TI}\left(T^{-2}\sum_{t=2}^{T}\hat{u}_{t-1}^2\right)^{\frac{1}{2}}} \xrightarrow{d} \xi_\eta \tag{10}$$

where $\hat{u}_t$, $\hat{\rho}$ and $\hat{v}_t$ are estimated from regression models (8) and (9), $s_v^2 = T^{-1}\sum_{t=2}^{T}\hat{v}_t$, s_{TI}^2 is an estimator of the spectral density at frequency zero of $\{u_t\}$. Specifically, $s_{TI}^2 := s_k^2/\left(1-\hat{\beta}(1)\right)^2$ where $s_k^2 = T^{-1}\sum_{t=p+1}^{T}\hat{k}_t$, $\hat{\beta}(1) := \sum_{i=1}^{p}\hat{\beta}_i$, with $\hat{\beta}_i$ and $\left\{\hat{k}_t\right\}$ are obtained from the autoregression:

$$\Delta\hat{u}_t = \rho_0\hat{u}_{t-1} + \sum_{i=1}^{p}\beta_i\Delta\hat{u}_{t-i} + k_t \tag{11}$$

As elaborated in the previous subsection, the critical value of ξ_η is not available because it depends on the nuisance parameter η_v. Similarly, Wang, Zhao, and Li (2019) proposed using the wild bootstrap algorithm to obtain the critical value, with its asymptotic validity also provided.

Asymmetric Vector Error Correction Model (VECM) and Asymmetric Effect

To investigate the potential asymmetric effect of sentiment on market liquidity, we employed a Vector Error Correction Model (VECM) with dummy variables representing positive and negative sentiment. The VECM allows us to capture how deviations from the cointegration equilibrium in Equation (8) are corrected over time. The error correction term ensures that any short-run deviations of TR are gradually adjusted, pushing the TR back toward the cointegration relationship.

The VECM is specified as:

$$\begin{aligned}\Delta TR_t = \delta_0 + \alpha_1(TR_{t-1} - \beta_1 NSI_{t-1}) + \alpha_2(TR_{t-1} - \beta_1 NSI_{t-1})D_{NSI} \\ + \sum_{i=1}^{k}\gamma_i\Delta TR_{t-i} + \sum_{i=1}^{k}\theta_i\Delta NSI_{t-i} + \eta_t\end{aligned} \tag{12}$$

where D_{NSI} a dummy variable that equals 1 when $NSI_t \geq 0$ (positive sentiment) and 0 when $NSI_t < 0$ (negative sentiment). The term $(TR_{t-1} - \beta_1 NSI_{t-1})$ represents the cointegration residual, which indicates how much TR deviates from the long-running cointegration equilibrium in the previous period.

When the coefficient α_1 is negative, its absolute value reflects the speed at which TR returns to the cointegration equilibrium. Specifically, when $(TR_{t-1} - \beta_1 NSI_{t-1})$ is negative, this indicates that TR is below its equilibrium value. In this case, the negative α_1 will result in a positive change in ΔTR_t. This change incrementally moves TR toward the equilibrium. Conversely, if $(TR_{t-1} - \beta_1 NSI_{t-1})$ is positive, indicating that TR is above equilibrium, the same negative α_1 will produce a decrease in ΔTR_t. This adjustment will push TR downwards, again moving it toward equilibrium.

To capture the potential asymmetric effect of sentiment, we introduced the term $\alpha_2(TR_{t-1} - \beta_1 NSI_{t-1}) D_{NSI}$. This term adjusts the model based on the positivity of sentiment expressed through D_{NSI}, a dummy variable indicating periods of positive sentiment. The coefficient α_1 represents the adjustment speed when sentiment is negative, while $\alpha_1 + \alpha_2$ represents the adjustment speed when sentiment is positive. Here, α_2 specifically modifies the adjustment mechanism to account for the impact of optimistic sentiment. α_2 measures the magnitude and direction of the asymmetric effect of sentiment on TR. If α_2 is significantly different from zero, it indicates that the impact of positive sentiment on liquidity differs from that of negative sentiment, thus confirming the existence of asymmetry. Briefly, the VECM framework not only describes the correcting for short-term deviations of TR from the long-run relationship but also enables us to measure the asymmetric effects of sentiment on market liquidity.

Empirical Results

Time-Varying Volatility and Unit Root Tests Results

In this section, we assessed whether NSI and TR display the time varying volatility first. As elaborated in Section "Methodology", we estimated $\hat{\eta}(s)$ of them, with the results presented in Figure 3. As previously mentioned, the 45° line serves as a benchmark for constant volatility. Therefore, any deviation from this line implies the existence of time-varying volatility. As observed in Figure 3, the presence of time-varying volatility features for these variables was confirmed.

Furthermore, to test whether NSI and TR follow a random walk, we employed the wild bootstrap ADF and MZ tests, with the results presented in Table 2. As shown, both the wild bootstrap ADF and MZ tests failed to reject the null hypothesis of a random walk at the 1% significance level. Thus, we concluded that both NSI_t and TR_t exhibit random walk dynamic behavior with time-varying volatility. Their corresponding first-differenced series, ΔNSI_t and ΔTR_t, are stationary, which collaborates the previous conclusion.

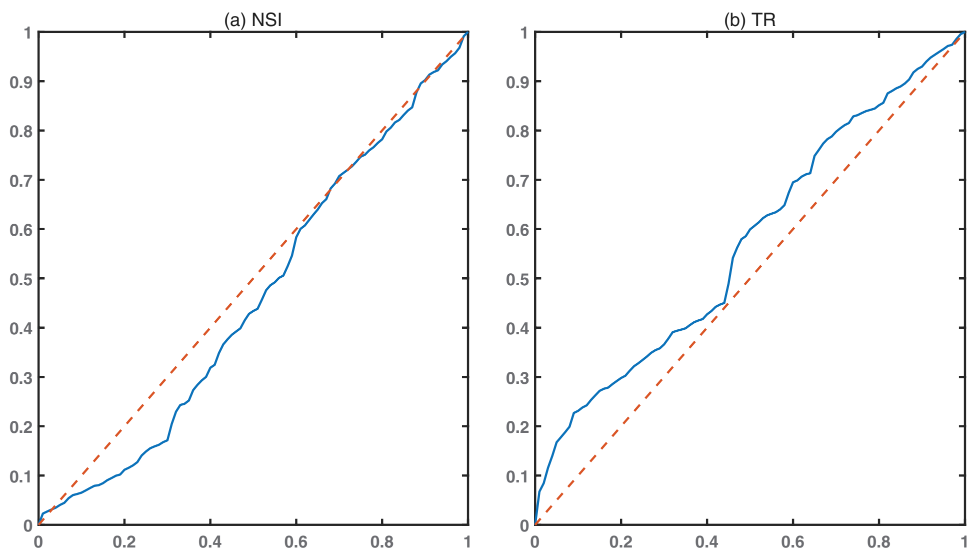

Figure 3. The variance profiles of NSI and TR. The 45° lines indicate constant volatility and the blue lines denote the variance profiles. The deviation from the 45° line of variance profiles implies time-varying volatility.

Table 2. The unit root test results for the NSI and TR.

	MZ test			ADF test		
	MZ_t	CV	PV	ADF	CV	PV
NSI_t	−1.583	−2.869	0.529	−1.741	−2.947	0.455
ΔNSI_t	−20.141	−2.010	0.000	−51.329	−1.980	0.000
TR_t	−1.278	−2.131	0.188	−1.502	−1.937	0.13
ΔTR_t	−19.749	−1.956	0.000	−55.144	−1.711	0.000

Notes: MZ_t and ADF represent the statistical values and CV represents the critical value using the wild bootstrap method at the 5% significance level; PV represents the p-value of the wild bootstrap test.

Notably, our conclusion offers a novel perspective on the stock market sentiment dynamics in China by unrevealing that investor sentiment follows a random walk process. We believe that the random walk process can better describe the inherently unpredictable nature of investor sentiment than the stationary process. Given its dynamic movements evolving without a deterministic trend, the random walk process could capture the dynamic, non-deterministic fluctuations of sentiment more effectively, which provides deeper insight into investor psychology. It is particularly relevant for understanding how sentiment reacts to market dynamics in real-time, adapts to unpredictable shocks, and exhibits volatility changes over time.

This is the first time that sentiment in the Chinese stock market has been explicitly characterized as a random walk with time-varying volatility. This conclusion not only extends the existing literature but also provides a more comprehensive understanding of investor psychology.

Cointegration Test Results and the Asymmetric Effect of NSI on TR

As demonstrated in Section "Methodology", we employed the wild bootstrap EG2 test to examine the cointegration relationship between the NSI and TR, with results presented in Table 3. To further check the robustness of the cointegration relationship, we conducted tests by alternately placing NSI and TR on the right-hand side of Equation (8). In each scenario, the null hypothesis of no cointegrating relationship was consistently rejected at the 1% significance level, affirming a stable and significant cointegration between the NSI and TR. This confirmed cointegration suggested that the sentiment is co-moved with the liquidity, which implies that changes in investor sentiment, especially those triggered by sudden shocks, are associated with corresponding changes in market liquidity.

Table 4 (Column 1) reports the estimates of Equation (12), revealing that sentiment (NSI) has an asymmetric impact on market liquidity (TR). In details, the TR adjusts to the cointegration

Table 3. Cointegration test with the wild bootstrap critical value.

	NSI_t on the right			TR_t on the right		
	Z_t	CV	P_τ^B	Z_t	CV	P_τ^B
NSI_t or TR_t	−6.579	−2.698	0.000	−6.578	−2.915	0.000

Notes: CV represents the critical value using the wild bootstrap method at the 5% level of significance; P_τ^B is the *P*-value of Z_t^B test based on the wild bootstrap method.

Table 4. The asymmetric effect of the NSI on the market liquidity.

	Estimated coefficient	Pre-COVID-19	Under-COVID-19
δ_0	0.0000	−0.0000	0.0000
β_1	−0.0008	−0.0003	−0.0016
α_1	−0.0704	−0.0820	−0.0485
α_2	0.0091	0.0393	0.0027

relationship asymmetrically, with daily recovery rates of 6.13% for positive sentiment and 7.04% for negative sentiment. This suggests that liquidity adjusts more quickly following negative sentiment compared to positive sentiment.

This asymmetry observed in effect may stem from two sources. First, investors, particularly noise traders, tend to react more strongly to bad news than good news (He 2022). Studies have shown that markets are generally more sensitive to negative news, which aligns with our findings (Chen and Ghysels 2011; Glosten, Jagannathan, and Runkle 1993; Nelson 1991; Wen et al. 2019). Second, in response to pessimistic sentiment, investors may reduce their trading positions, leading to a decrease in liquidity. This reduction in trading activity causes market turnover rates to adjust more quickly to the lower liquidity levels. Collectively, these factors contribute to the observed faster market adjustment under negative sentiment. Therefore, we claimed that our findings of the co-movement of sentiment with liquidity, along with the asymmetric effect, have updated and extended current studies.

The COVID-19 Narrows the Asymmetric Effect of NSI on TR

To study whether the impact of sentiment on liquidity has been changed during the COVID-19 pandemic, we chose two sample periods: pre-COVID-19 (January 2016 to December 2019) and during COVID-19 (December 2019 to December 2022). Our analysis, detailed in Columns 2 and 3 of Table 4, utilized Equation (12) to quantify how TR adjusted to changes in the NSI across these periods. Before the pandemic, the adjustment rate was 8.20% under pessimism and 4.28% under optimism, indicating a significant asymmetry in effect of sentiment on liquidity. During the pandemic, the adjustment rates reduced to 4.85% under pessimism, and increased slightly to 4.57% under optimism. Overall, the asymmetry in the effect has been narrowed during the COVID-19 pandemic. Intuitively, liquidity responses to sentiment became slower under pessimism during the pandemic.

Two primary factors may explain the changes observed during the pandemic. First, the heightened uncertainty during the epidemic made investors more cautious in response to negative sentiment. This reduced investor sensitivity significantly decreased the adjustment speed of the TR under pessimistic conditions, thereby narrowing the asymmetry. Second, optimism bias—the tendency to overestimate positive outcomes (Weinstein 1980)—provides another perspective. This bias has been shown to be more prevalent during widespread crises like the pandemic (Fischhoff et al. 2018; Ji et al. 2004; Johnson 2017). It has been well documented that this tendency was particularly strong during COVID-19 pandemic (Dolinski et al. 2020; Druică, Musso, and Ianole-Călin 2020; Kohút, Šrol, and Čavojová 2022; Kuper-Smith et al. 2021), especially in China, where the government's strict COVID-19 control measures reinforced investor confidence (Bansal 2020; Dolinski et al. 2020; Shukla, Mishra, and Rai 2021). As a result, the market became more sensitive to positive news, further reducing the asymmetry between responses to pessimistic and optimistic sentiment.

Therefore, we concluded that the asymmetry in the effect of sentiment on liquidity has been reduced during COVID-19 pandemic. In another words, the difference between reactions to positive and negative sentiment has been narrowed. However, how the asymmetry was reduced still remains as an open issue. We suggest that future research could explore whether this is a consistent circumstance across other types of crises, such as financial crises, which could contribute to a more comprehensive understanding of sentiment's role.

Conclusions

This study constructed the NSI for the Chinese stock market using data from GDELT, which aligns well with stock market movements and captures major market events effectively. Moreover, we have used the NSI to provide insights into the dynamic evolution of sentiment. At the meantime, its relationship with key market variables, namely the liquidity, has been investigated. Our conclusions can be regarded as fourfold:

First, our findings deepen the understanding of market sentiment dynamics by illustrating that the NSI exhibits time-varying volatility and follows a random walk pattern. This reflects the unpredictability inherent in investors' psychology driven by news shocks. Such insights are crucial for regulatory bodies and financial market overseers, as they underscore the necessity of policies that enhance transparency and information dissemination. By improving the timeliness and accuracy of financial disclosures and strengthening news verification mechanisms, regulators could help stabilize investor reactions and reduce the volatility induced by rapid shifts in sentiment.

Second, we supplemented the existing literature regarding the relationship between the sentiment and the market dynamics by unveiling that the NSI and market liquidity are cointegrated, which indicates a long-term co-movement between sentiment and liquidity. This finding is pivotal for the development of market infrastructure that supports robust liquidity management. Technologies like real-time liquidity monitoring systems could be instrumental in preempting liquidity crises triggered by sudden sentiment-driven market movements, thereby enhancing overall market stability.

Third, we newly found that the NSI impacts liquidity asymmetrically. Specifically, the TR adjusts to the cointegration relationship with a daily recovery rate of 6.13% for positive sentiment, while the adjustment speed is faster under negative sentiment at 7.04%. This asymmetric recovery suggests that market policies should consider facilitating quicker stabilization following declines, while ensuring these interventions do not inhibit the natural market adjustments during periods of rising sentiment. This approach helps maintain a balanced market response during various sentiment phases, thereby supporting a stable trading environment.

Finally, during the COVID-19 pandemic, we first revealed that the asymmetry between reactions to pessimistic and optimistic sentiment narrowed. This shift is likely due to heightened uncertainty causing cautious trading under pessimism. Additionally, optimism bias during the pandemic, especially in China, led to increased sensitivity to positive sentiment, further reducing the difference in responses. This finding suggests that traders have become more cautious under pessimistic scenarios and show increased sensitivity to positive news, a trend particularly noted in China during the pandemic. For policymakers, this observation emphasizes the importance of developing adaptable regulatory frameworks that can swiftly respond to changing market conditions and manage investor reactions effectively to prevent overreactions.

Notes

1. As of August 2023, foreign investors held A-shares worth 3.5 trillion yuan, accounting for 9% of the free float market capitalization, with 1 trillion yuan held through the QFII/RQFII system.
2. The GDELT database can be accessed through Google BigQuery (https://cloud.google.com/bigquery/).
3. For more information on GDELT theme labels, see: http://data.gdeltproject.org/documentation/GDELT-Global_Knowledge_Graph_CategoryList.xlsx. and https://blog.gdeltproject.org/new-august-2019-gkg-2-0-themes-lookup/.
4. Unlike Shen et al. (2022), who only included Chinese-language news, we considered news from all languages, believing that sentiment expressed in non-Chinese languages, including English, can significantly impact the Chinese stock market.

Disclosure Statement

No potential conflict of interest was reported by the author(s).

Funding

This work was supported by the National Natural Science Foundation of China under Grant [number 72173048] and Huazhong University of Science and Technology Double First-Class Funds for Humanities and Social Sciences.

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