“The impact of investor sentiment on stock liquidity of listed companies in China”

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THE IMPACT OF INVESTOR SENTIMENT ON STOCK LIQUIDITY OF LISTED COMPANIES IN CHINA

Abstract

Researchers have scrutinized the link between investor sentiment and stock market liquidity globally, yet few have delved into this dynamic in emerging markets, especially China. Utilizing a sample of 1,839 publicly listed companies in China from 2010 to 2019, this study applies firm- and year-fixed-effects models to explore the nexus between investor sentiment and stock illiquidity, employing the Amihud measure for stock illiquidity assessment. The outcomes of these fixed-effect regressions illustrate a significantly positive relationship between investor sentiment and stock liquidity in the Chinese market. The positive link is more evident in scenarios characterized by high firm leverage, rapid revenue growth, larger corporations, greater institutional ownership, higher stock volatility, and lower book-to-market ratios. Intriguingly, this analysis incorporates the quadratic term of investor sentiment to examine the potential for a nonlinear dynamic between stock illiquidity and investor sentiment. The findings elucidate that the effect of investor sentiment on stock liquidity diminishes at elevated levels of sentiment, revealing a nonlinear inverse U-shaped relationship. The positive correlation between investor sentiment and stock liquidity persists across the three divisions of the Chinese Shenzhen Stock Exchange and remains robust using alternative liquidity measures, such as Roll's impact and zeros impact. Addressing causality concerns, current investor sentiment appears to influence subsequent liquidity levels. These results provide valuable perspectives for policymakers, business executives, and investors in the stock market.

Keywords investor sentiment, stock liquidity, Amihud illiquidity, market microstructure, nonlinear relationship, emerging markets, China

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INTRODUCTION

The exploration of investor sentiment as a critical influencer of stock market dynamics has garnered significant attention, with seminal contributions like those from Barberis et al. (1998) underscoring the profound impact of news and information on investor reactions. This discourse has revealed a nuanced landscape where not all market demand is rooted in rational analysis, as highlighted by Canbaş and Kandır (2009), who found that much of it is swayed by investor expectations and sentiment. This divergence from rational behavior, often led by "noise" as characterized by Black (1986), introduces a pivotal challenge to the traditional finance paradigm that Barberis and Thaler (2003) describe as being dominated by the concept of "rational agents." The manifestation of pronounced irrationality among investors, notably within the Chinese market, suggests potential limitations of the efficient market hypothesis in capturing real-time asset price adjustments to their actual equilibrium values. While behavioral finance and market microstructure theories have begun to bridge these gaps, identifying a clear linkage between investor sentiment and market liquidity, a significant portion of this inquiry has been skewed toward the U.S. stock market. This leaves a conspicuous void in understanding these dynamics within emerging markets, particularly China, where market behavior may present unique characteristics and challenges. This study seeks to pivot from this predominant focus, delving into the intricate relationship between investor sentiment and stock liquidity in China's evolving financial landscape.

1. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

The influence of investor sentiment on market liquidity has emerged as a notable and significant study area. This study examines pertinent literature on market liquidity, investor sentiment, and the interplay between these variables.

Initially, Kyle (1985) delineated "liquidity" as the inverse of price sensitivity to order flow. Subsequently, Amihud and Mendelson (1986) adopted the bid-ask spread as a measure of liquidity, deducing that a narrower spread indicates higher market liquidity. Amihud (2002) further characterized illiquidity as the ratio of a stock's absolute daily return to its daily dollar volume, computed as an average over a specific timeframe. This can be understood as the daily stock price's response to a unit dollar of trading volume. However, Brunnermeier and Pedersen (2009) identified two distinct types of liquidity. Market liquidity is the ease of trading an asset, whereas funding liquidity relates to traders' ability to secure financing. Valenzuela et al. (2015) recently introduced a novel approach termed "relative liquidity" for evaluating market liquidity. This innovative metric considers the distribution of quoted depth in a limit order book and gauges the consensus level on a security's trading price. Goyenko et al. (2009) initiated their analysis with high-frequency indicators, introducing two additional dimensions to all liquidity metrics, spanning from transaction costs to price shocks. Liquidity calculation methods can be bifurcated into two categories: direct indicators derived from high-frequency trading data and indirect indicators stemming from low-frequency data analysis. These innovative approaches to measurement and the expanded classification of liquidity have infused numerous fresh perspectives into the field.

In recent years, more studies on market liquidity have begun to explore its influence on asset price dynamics and leverage. Regarding asset price behavior, Cespa and Foucault (2014) demonstrated a mutually reinforcing positive relationship between price informativeness and liquidity. This interplay leads to liquidity spillovers and creates a vulnerability. A slight decrease in an asset's liquidity can precipitate a substantial loss in overall market liquidity and price informativeness. This interconnection offers a new perspective in understanding liquidity co-movements and the occurrences of liquidity dry-ups. In terms of leverage, Acharya and Viswanathan (2011) noted that financial entities often opt for highly leveraged financing in transactions. Such practices lead to swift fluctuations in market liquidity. Intriguingly, this pattern is observed widely across the market. Suresha et al. (2022) demonstrated that environmental, social, and governance practices significantly bolster stock liquidity within the Indian stock market.

Several studies have examined market liquidity in the Chinese stock market. Zhang et al. (2023) uncovered that increased economic policy uncertainty correlates with reduced stock liquidity, a phenomenon more pronounced in firms characterized by opaque information environments, diminished investor attention, and limited risk resilience. Yang et al. (2023) focused on 338 companies listed under the Chinese carbon emission trading market, unveiling a positive spillover effect of carbon price liquidity on stock liquidity. Cai and Zhang (2023) explored the impact of the COVID-19 pandemic on the liquidity of Chinese corporate bonds, finding a significant adverse effect. Liang et al. (2023) observed that environmental, social, and governance ratings have a markedly negative influence on stock liquidity risk in the agricultural sector and other industries within the Chinese market. These discussions underscore that while liquidity was established years ago, its measurement and classification have continually evolved. With the advent of behavioral finance, numerous liquidity-related issues are now being linked to this emerging field. Consequently, the following paragraph will begin reviewing the literature about investor sentiment.

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Investor sentiment refers to investors' collective mood or outlook towards a particular financial market or security, manifesting as optimism, pessimism, or neutrality. Although a relatively nascent concept in finance, its precise definition remains elusive. Initially posited by De Long et al. (1990), investor sentiment was described as an investor's erroneous expectation regarding an asset's fundamental value. Subsequently, Baker and Stein (2004) characterized investor sentiment as a distortion in the perceived fundamental value of future assets. They posited that market liquidity could serve as a barometer of sentiment in contexts where short sales face constraints. In markets of exceptional liquidity, irrational investors often influence pricing and display a tendency to underreact to information inherent in order flow or equity issues. Consequently, elevated liquidity levels suggest a predominantly optimistic stance among these irrational investors, correlating with notably diminished expected returns. Furthering this discourse, Baker and Wurgler (2006) interpreted investor sentiment as the overarching positive or negative outlook toward the impending stock market landscape. Their study developed a novel sentiment index and explored its influence on the cross-sectional variation in stock returns, noting a dependency on sentiment proxies measured at period commencement. Additionally, they observed that when sentiment is assessed as high, stocks that resonate with speculators yet are unattractive to arbitrageurs tend to yield lower returns.

Amidst technological advancements, more individuals are now employing search frequency, text analysis, and other previously unavailable technologies to gauge investor sentiment. Joseph et al. (2011) utilized online stock query records to predict investor sentiment and stock trading volumes. Karabulut (2013) adopted Facebook's gross national happiness (GNH) as a novel sentiment proxy to forecast daily returns and trading volumes in the U.S. stock market. Da et al. (2015) constructed an index of financial and economic attitudes revealed by search (FEARS), incorporating select negative terms such as "recession," "bankruptcy," and "unemployment." In the context of China, Zhao and Zhang (2024) employed the Google search index as an indicator of individual investor sentiment.

Researchers have acknowledged the significant impact of investor sentiment on the stock market, influencing aspects like stock returns, volatility, liquidity, and other factors. Karabulut (2013) discovered that an increase in GNH correlates with higher daily returns on the subsequent day, but this trend reverses in the following days. Da et al. (2015) also demonstrated that the FEARS index can predict overall market returns. Notably, the FEARS index is associated with lower returns today but can indicate higher returns tomorrow. This effect is particularly pronounced in stocks favored by sentiment-driven investors and those most challenging to arbitrage. Kim et al. (2014) observed that there is a stronger predictability of stock returns based on disagreement during periods of high sentiment. Johnman et al. (2018) applied text analysis to determine if positive and negative sentiment indicators could predict daily excess returns and volatility in the FTSE 100 index. They also evaluated the economic value of these indicators through a trading strategy that incorporated them. Their results indicated that while sentiment measures do not influence excess returns, they affect volatility, with negative sentiment increasing volatility and positive sentiment reducing it. Firth et al. (2014) examined the implications of investor sentiment on asset pricing in Chinese financial markets, noting that in risky market conditions, investors maintaining a positive outlook and not succumbing to herd behavior are better equipped to adapt to market changes due to the influence of investor sentiment on decision-making and execution. From these reviews, it is evident that investor sentiment has sparked extensive debate among scholars. There are diverse approaches to conceptualizing investor sentiment and contradictions regarding its impact on stock returns. The ensuing discussion will focus on the effect of investor sentiment on stock market liquidity.

The effects of investor sentiment on stock market liquidity manifest in two distinct ways: direct and indirect influences. De Long et al. (1990) theorized that elevated investor sentiment heightens noise trading, enhancing market liquidity. Baker and Stein (2004), building on behavioral finance and noise trading theories, developed a model that revealed that when the sentiment of irrational investors turns positive, their trading frequency increases, thereby augmenting market liquidity. Regarding indirect influence, Odean (1998) suggested that heightened investor sentiment might signal elevated market overconfidence, leading to increased stock market liquidity. Liu (2015) examined roughly 150 weekly newsletters, categorizing them as bullish, bearish, or neutral, and employed the variance between bullish and bearish ratios to measure sentiment. His study established a distinct correlation, demonstrating that elevated investor sentiment correlates with increased market trading volume. Asem et al. (2016) explored this relationship within the Australian context, discovering that a decrease in investor sentiment heightens concerns about illiquidity, thereby increasing the required compensation for holding illiquid assets. Debata et al. (2018) analyzed sample data from twelve diverse emerging stock markets, uncovering a positive correlation between investor sentiment and liquidity in these markets, with foreign investor sentiment significantly influencing the liquidity of emerging stock markets. Chiu et al. (2018) investigated this relationship during the financial crisis, finding that elevated optimism enhances stock liquidity. They also noted that financing constraints may intensify the asymmetric response of stock liquidity and investor trading behavior to investor sentiment during the financial crisis.

Few studies have identified a negative correlation between investor sentiment and stock market liquidity. Dunham and Garcia (2021) employed firm-level investor sentiment ratings derived from news and Twitter content to analyze liquidity fluctuations in regression models. They discovered substantial evidence indicating that firm-level investor sentiment, as gauged from Twitter, is inversely related to stock liquidity. Wang et al. (2023) discovered that air pollution adversely impacts investors. Consequently, in response to negative emotions, investors tend to adopt passive strategies, reducing liquidity in the stock market. Additionally, their research reveals that stock market liquidity and air quality share an inverse U-shaped relationship. In summary, the ensuing hypothesis is proposed, considering that most existing research indicates a positive correlation between investor sentiment and stock market liquidity.

H1: Investor sentiment positively impacts the stock liquidity of listed companies in China.

2. METHODOLOGY

The study employs data from two sources: (1) the China Stock Market & Accounting Research (CSMAR) Database and (2) the Wind Economic Database. The sample period spans from 2010 to 2019, with an annual sampling frequency. The selection of 2019 as the terminal year is due to the potentially significant impact of COVID-19 on investor sentiment. The sample excludes financial firms due to their distinctive capital structures and omits Special Treatment companies facing imminent delisting risks. The final sample comprises 10,546 firm-year observations, representing 1,839 distinct firms.

The dependent variable, stock illiquidity, is retrieved from the CSMAR database. Following Amihud (2002), stock illiquidity is defined as the daily price response of a stock to a dollar of trading volume:

$$Illiq_{i,t} = \frac{1}{D_{i,t}} \sum_{s=1}^{D_{i,t}} \frac{\left|R_{i,t,d}\right|}{Volume_{i,t,d}}, \tag{1}$$

where $D_{i,t}$ is the number of the effective trading days of stock i in year t, $\left|R_{i,t,d}\right|$ is the absolute value of the return rate of the stock i in year t and day d, $Volume_{i,t,d}$ is the trading volume of stock i in year t and day d. Alternatively, Roll's impact illiquidity measure is articulated following Roll (1984) and Fernández-Amador et al. (2013):

$$Roll_{i,t} = \begin{cases} \dfrac{2\sqrt{-Cov\left(\Delta P_{i,t,d}, \Delta P_{i,t,d-1}\right)}}{Avg\left(Volume_{i,t,d}\right)}, & \text{if } Cov\left(\Delta P_{i,t,d}, \Delta P_{i,t,d-1}\right) < 0 \\ 0, & \text{if } Cov\left(\Delta P_{i,t,d}, \Delta P_{i,t,d-1}\right) \geq 0 \end{cases} \tag{2}$$

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where $\Delta P_{i,t,d}$ is the change in the price of stock i in year t and day d, $Avg(Volume_{i,t,d})$ is the daily average trading volume of stock i in year t, Cov is the covariance of the price changes between two consecutive days. Finally, zeros impact illiquidity measure is defined as follows.

$$Zeros_{i,t} = \frac{N_{0,i,t}/N_{i,t}}{Avg\left(Volume_{i,t,d}\right)}, \tag{3}$$

where $N_{0,i,t}$ is the number of zero daily returns for stock i in year t, and $N_{i,t}$ is the total number of trading days for stock i in year t,

Utilizing data from Wind, we acquire three variables essential for constructing the independent variable, investor sentiment. Barberis et al. (1998) articulate that investor sentiment is the systematic anticipation that securities prices will diverge from their fundamentals, driven by inherent cognitive biases and constrained rationality. Consequently, the disparity between a company's intrinsic value and current market valuation is utilized to assess investor sentiment. Therefore, as Rhodes-Kropf et al. (2005) outlined, firms' market valuation is divided into the intrinsic value component and the mispricing component under market sentiment. This division forms the basis of the subsequent model for annual and sectoral regression to derive indicators of investor sentiment:

$$\begin{aligned} MktValue_{i,t} &= \beta_0 + \beta_1 FirmSize_{i,t} \\ &+ \beta_2 Lev_{i,t} + \beta_3 \ln\left(ROA_{i,t}\right) + \varepsilon_{i,t}, \end{aligned} \tag{4}$$

where i represents company i and t indicates year t. *MktValue* denotes the natural logarithm of the company's market value, *FirmSize* reflects the natural logarithm of the firm's total assets, *Lev* signifies the firm's leverage, defined as the ratio of debt to assets, *ROA* represents the return on assets, calculated as net income over total assets, and ε is the residual term. The predicted *MktValue* represents the firm's intrinsic value. Standardizing the residual, which is the difference between actual and predicted *MktValue*, allows for assessing a stock's mis-valuation relative to industry counterparts, serving as an index for investor sentiment (*Senti*).

The relationship between stock market illiquidity (*Illiq*) and investor sentiment (*Senti*) is examined via the subsequent multivariate regression equation:

$$\begin{aligned} Illiq_{i,t} &= \beta_0 + \beta_1 Senti_{i,t} + \beta_2 Lev_{i,t} \\ &+ \beta_3 RevGrow_{i,t} + \beta_4 FirmSize_{i,t} \\ &+ \beta_5 InstOwn_{i,t} + \beta_6 BM_{i,t} + \beta_7 ROA_{i,t} \\ &+ \beta_8 Volatility_{i,t} + FirmFE + YearFE + \varepsilon_{i,t}, \end{aligned} \tag{5}$$

where *RevGrow* is the growth rate of revenue, *InstOwn* is the institutional ownership defined as the ratio of shares held by institutions to the outstanding shares, *BM* is the book-to-market ratio, *Volatility* is the stock volatility defined as the standard deviation of daily stock returns, *FirmFE* represents firm fixed effects using a series of firm dummies, and *YearFE* represents year fixed effects using a series of year dummies. If both firm- and year-fixed effects are overlooked, ordinary least squares regressions with robust standard errors are utilized.

3. RESULTS

Table 1 presents the statistics for the sample variables. The mean *Amihud* illiquidity is 0.047, closely aligned with its standard deviation 0.044. The average *Senti* stands at 0.707, significantly exceeding its standard deviation 0.014. This indicates that the illiquidity measure demonstrates broader variability than the sentiment measure. The average leverage ratio is 41.5%, the revenue growth rate is 16.1%, the mean logarithm of total assets is 22.211, institutional ownership is relatively low at 6.8%, the average book-to-market ratio is moderate at 0.620, the return on assets is 4.2%, and stock volatility is 2.8%.

Table 2 exhibits the correlations between all variables. The correlations of *Senti* with both *Illiq* and *Roll* are negative and statistically significant at the 1% level, yet the correlation between *Senti* and the *Zeros* illiquidity measure is not significant. The illiquidity measure displays a significantly negative correlation with most control variables. It logically follows that high revenue growth, larger firm size, and higher return on assets all contribute to increased liquidity.

Table 1. Descriptive statistics

Variable	Obs.	Mean	Std.Dev.	Min	P25	Med	P75	Max
Illiq	10,546	0.047	0.044	0.004	0.018	0.033	0.062	0.332
Roll	10,546	0.053	0.013	0.019	0.043	0.052	0.061	0.122
Zeros	10,546	0.026	0.022	0.000	0.012	0.020	0.033	0.212
Senti	10,546	0.707	0.014	0.617	0.703	0.709	0.713	0.754
Lev	10,546	0.415	0.188	0.060	0.264	0.413	0.562	0.823
RevGrow	10,546	0.161	0.251	-0.361	0.007	0.121	0.269	1.326
FirmSize	10,546	22.211	1.096	20.186	21.402	22.075	22.895	25.696
InstOwn	10,546	0.068	0.084	0.000	0.007	0.034	0.098	0.420
BM	10,546	0.620	0.220	0.174	0.443	0.619	0.793	1.090
ROA	10,546	0.042	0.037	-0.094	0.018	0.038	0.063	0.154
Volatility	10,546	0.028	0.008	0.014	0.023	0.027	0.032	0.058

Note: This table presents descriptive statistics of the annual sample spanning 2010 to 2019. *Illiq* denotes Amihud's illiquidity metric, *Roll* denotes Roll's illiquidity measure, *Zeros* characterizes the illiquidity metric based on zero return days, *Senti* reflects investor sentiment, and *Lev* represents firm leverage as indicated by the debt ratio, *RevGrow* captures the rate of revenue growth, *FirmSize* signifies the logarithm of firm assets, *InstOwn* illustrates institutional ownership, *BM* defines the book-to-market ratio, *ROA* typifies the return on assets, and *Volatility* portrays the stock's volatility.

Table 2. Pairwise correlations

	Illiq	*Roll*	*Zeros*	*Senti*	*Lev*	*RevGrow*	*FirmSize*	*InstOwn*	*BM*	*ROA*	*Volatility*
Illiq	1										
Roll	–0.161***	1									
	(0.000)										
Zeros	0.100***	–0.414***	1								
	(0.000)	(0.000)									
Senti	–0.386***	–0.026***	0.011	1							
	(0.000)	(0.007)	(0.258)								
Lev	–0.142***	–0.086***	0.178***	–0.012	1						
	(0.000)	(0.000)	(0.000)	(0.220)							
RevGrow	–0.053***	0.045***	–0.118***	–0.011	0.031***	1					
	(0.000)	(0.000)	(0.000)	(0.268)	(0.002)						
FirmSize	–0.436***	–0.202***	0.267***	0.187***	0.555***	–0.006	1				
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.559)					
InstOwn	–0.119***	0.041***	–0.265***	0.062***	–0.059***	0.206***	0.032***	1			
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)				
BM	0.182***	–0.392***	0.431***	–0.104***	0.376***	–0.082***	0.508***	–0.219***	1		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			
ROA	–0.073***	–0.057***	–0.201***	0.074***	–0.361***	0.198***	–0.073***	0.328***	–0.272***	1	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
Volatility	–0.082***	0.887***	–0.445***	–0.079***	–0.075***	0.028***	–0.218***	0.072***	–0.407***	–0.070***	1
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)	

Note: This table shows the pairwise correlations between variables. The *p*-values are reported in parentheses below the correlation coefficients. ***, **, and * denote statistical significance levels of 1%, 5%, and 10%, respectively.

Equation (5) is employed for univariate (or multivariate) ordinary least squares (or fixed-effects) regressions. The results in Table 3 indicate that investor sentiment significantly and negatively impacts stock illiquidity. The regression coefficient for *Senti* is –0.854. An elevation of one standard deviation in *Senti* (0.014) leads to an approximate decrease of 0.012 in stock illiquidity (=0.854×0.014), which constitutes about 26% of the mean stock illiquidity (=0.012/0.047). This underscores the considerable economic influence of investor sentiment on stock illiquidity. The coefficients for the control variables are then examined. Consistent with expectations, larger firm size and higher return on assets are associated with lower illiquidity (high liquidity). Increased leverage correlates with

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reduced liquidity. Contrary to intuition, greater institutional ownership, a higher book-to-market ratio, and lower stock volatility are associated with greater stock illiquidity (low liquidity). Overall, the baseline regression results in Table 3 support Hypothesis 1.

Table 3. Baseline regressions

	(1)	(2)	(3)	(4)
	Illiq	*Illiq*	*Illiq*	*Illiq*
Senti	–1.233***	–0.878***	–0.693***	–0.854***
	(0.050)	(0.059)	(0.050)	(0.057)
Lev			0.017***	0.014***
			(0.002)	(0.004)
RevGrow			–0.006***	0.002
			(0.001)	(0.001)
FirmSize			–0.027***	–0.030***
			(0.001)	(0.001)
InstOwn			0.011***	0.021***
			(0.004)	(0.005)
BM			0.094***	0.075***
			(0.002)	(0.003)
ROA			0.053***	–0.028**
			(0.010)	(0.013)
Volatility			–0.244***	–0.708***
			(0.042)	(0.075)
Constant	0.918***	0.665***	1.082***	1.272***
	(0.035)	(0.042)	(0.030)	(0.048)
Firm FE	No	Yes	No	Yes
Year FE	No	Yes	No	Yes
Observations	10,546	10,546	10,546	10,546
R-squared	0.149	0.435	0.458	0.531

Note: The table presents the results from regression analysis of stock illiquidity on investor sentiment and various control variables. Robust standard errors are indicated in parentheses below the estimated coefficient of each variable. *, **, and *** represent statistical significance levels at 10%, 5%, and 1%, respectively.

To assess the existence of a nonlinear relationship between stock illiquidity and investor sentiment, the following regression equation is employed:

$$\begin{aligned} Illiq_{i,t} &= \beta_0 + \beta_1 Senti_{i,t} + \beta_2 Senti_{i,t}^2 \\ &+ \beta_3 Lev_{i,t} + \beta_4 RevGrow_{i,t} + \beta_5 FirmSize_{i,t} \\ &+ \beta_6 InstOwn_{i,t} + \beta_7 BM_{i,t} + \beta_8 ROA_{i,t} \\ &+ \beta_9 Volatility_{i,t} + FirmFE + YearFE + \varepsilon_{i,t}. \end{aligned} \tag{6}$$

The results in Table 4 reveal that the regression coefficients for *Senti* consistently display negative and statistically significant values. The coefficients for *Senti*^{2} are positively significant, suggesting a nonlinear, U-shaped relationship between stock illiquidity and investor sentiment. This indicates that stock illiquidity decreases at a diminishing rate with increasing investor sentiment. As investor sentiment intensifies, its negative impact on stock illiquidity becomes less marked.

Table 4. Nonlinear quadratic regressions

	(1)	(2)	(3)	(4)
	Illiq	*Illiq*	*Illiq*	*Illiq*
Senti	–48.741***	–35.155***	–38.872***	–29.614***
	(2.187)	(1.697)	(1.716)	(1.629)
Senti^2	34.226***	24.738***	27.482***	20.756***
	(1.572)	(1.223)	(1.230)	(1.173)
Lev			0.022***	0.015***
			(0.002)	(0.004)
RevGrow			–0.006***	0.002*
			(0.001)	(0.001)
FirmSize			–0.025***	–0.026***
			(0.000)	(0.001)
InstOwn			0.004	0.020***
			(0.003)	(0.005)
BM			0.088***	0.060***
			(0.002)	(0.003)
ROA			0.042***	–0.045***
			(0.009)	(0.012)
Volatility			–0.176***	–0.686***
			(0.037)	(0.070)
Constant	17.393***	12.530***	14.288***	11.148***
	(0.761)	(0.589)	(0.598)	(0.563)
Firm FE	No	Yes	No	Yes
Year FE	No	Yes	No	Yes
Observations	10,546	10,546	10,546	10,546
R-squared	0.291	0.520	0.546	0.589

Note: This table delineates the nonlinear quadratic regression analysis of stock illiquidity on investor sentiment, the squared term of investor sentiment, and various control variables. Robust standard errors are shown in parentheses beneath the estimated coefficient of each variable. *, **, and *** represent statistical significance levels at 10%, 5%, and 1%, respectively.

Following Wang et al. (2024), the interaction terms between the independent variable *Senti* and each control variable have been integrated to evaluate their respective marginal impacts:

$$\begin{aligned} Illiq_{i,t} &= \beta_0 + \beta_1 Senti_{i,t} + \beta_2 Senti_{i,t} \\ &\times Control_{i,t} + \beta_3 Lev_{i,t} + \beta_4 RevGrow_{i,t} \\ &+ \beta_5 FirmSize_{i,t} + \beta_6 InstOwn_{i,t} + \beta_7 BM_{i,t} \\ &+ \beta_8 ROA_{i,t} + \beta_9 Volatility_{i,t} + FirmFE \\ &+ YearFE + \varepsilon_{i,t}, \end{aligned} \tag{7}$$

where *Control* denotes *Lev*, *RevGrow*, *FirmSize*, *InstOwn*, *BM*, *ROA*, and *Volatility*, respectively.

The results in Table 5 demonstrate that the regression coefficients of most interaction terms are significant. However, an exception arises with the coefficient for the interaction between *Senti* and *ROA*, which is insignificant. The adverse effect of investor sentiment on stock illiquidity intensifies with increased leverage, elevated revenue growth, larger firm size, greater institutional ownership, heightened stock volatility, and a reduced book-to-market ratio.

Table 6 elucidates the fixed-effects regression outcomes linking stock illiquidity and investor sentiment across three stock submarkets: the growth enterprise market (GEM) board, the small and medium enterprises (SME) board, and the main board. These findings indicate that investor sentiment significantly negatively influences stock illiquidity across all three boards, implying that the outcomes are consistent and robust across various stock categories.

Table 5. Moderating effects of control variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Illiq	***Illiq***	***Illiq***	***Illiq***	***Illiq***	***Illiq***	***Illiq***
Senti	−0.550***	−0.788***	5.254***	−0.761***	−1.168***	−0.845***	0.077
	(0.095)	(0.064)	(1.306)	(0.065)	(0.173)	(0.085)	(0.149)
Senti×Lev	−0.922***						
	(0.231)						
Senti×RevGrow		−0.387**					
		(0.154)					
Senti×FirmSize			−0.288***				
			(0.061)				
Senti×InstOwn				−1.500***			
				(0.411)			
Senti×BM					0.485**		
					(0.240)		
Senti×ROA						−0.230	
						(1.264)	
Senti×Volatility							−31.675***
							(4.919)
Lev	0.664***	0.015***	0.013***	0.015***	0.014***	0.014***	0.014***
	(0.162)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
RevGrow	0.002	0.275**	0.002	0.002	0.002	0.002	0.002
	(0.001)	(0.109)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
FirmSize	−0.030***	−0.030***	0.174***	−0.030***	−0.030***	−0.030***	−0.030***
	(0.001)	(0.001)	(0.044)	(0.001)	(0.001)	(0.001)	(0.001)
InstOwn	0.021***	0.021***	0.020***	1.080***	0.021***	0.021***	0.017***
	(0.005)	(0.005)	(0.005)	(0.291)	(0.005)	(0.005)	(0.005)
BM	0.075***	0.074***	0.076***	0.074***	−0.268	0.075***	0.077***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.170)	(0.003)	(0.003)
ROA	−0.027**	−0.027**	−0.024*	−0.026**	−0.027**	0.135	−0.026*
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.895)	(0.013)
Volatility	−0.701***	−0.701***	−0.692***	−0.711***	−0.714***	−0.708***	21.677***
	(0.075)	(0.075)	(0.074)	(0.075)	(0.075)	(0.075)	(3.479)
Constant	1.050***	1.224***	−3.060***	1.209***	1.495***	1.264***	0.620***
	(0.073)	(0.052)	(0.927)	(0.052)	(0.126)	(0.065)	(0.107)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,546	10,546	10,546	10,546	10,546	10,546	10,546
R-squared	0.534	0.532	0.536	0.533	0.532	0.531	0.541

Note: This table displays the results of the fixed-effects regression analysis of stock illiquidity on investor sentiment, various interaction terms, and control variables. The robust standard errors are disclosed in parentheses beneath the estimated coefficient of each variable. *, **, and *** indicate statistical significance levels at 10%, 5%, and 1%, respectively.

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Table 6. Different stock submarkets

	(1)	(2)	(3)
	GEM board	SME board	Main board
	Illiq	*Illiq*	*Illiq*
Senti	–0.580***	–1.088***	–0.829***
	(0.130)	(0.104)	(0.082)
Lev	0.043***	0.004	0.024***
	(0.007)	(0.009)	(0.007)
RevGrow	–0.001	0.002	0.004*
	(0.002)	(0.003)	(0.002)
FirmSize	–0.025***	–0.031***	–0.031***
	(0.002)	(0.003)	(0.002)
InstOwn	0.028***	0.017*	0.005
	(0.008)	(0.009)	(0.009)
BM	0.057***	0.093***	0.060***
	(0.005)	(0.007)	(0.005)
ROA	–0.008	–0.053**	–0.056**
	(0.021)	(0.025)	(0.024)
Volatility	–0.705***	–0.761***	–0.783***
	(0.130)	(0.139)	(0.120)
Constant	0.966***	1.449***	1.287***
	(0.096)	(0.103)	(0.063)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	3,497	3,022	4,027
R-squared	0.446	0.561	0.594

Note: The table presents the results from regression analysis of stock illiquidity on investor sentiment and various control variables across three distinct stock submarkets: the growth enterprise market (GEM) board, the small and medium enterprises (SME) board, and the main board. Robust standard errors are indicated in parentheses below the estimated coefficient of each variable. *, **, and *** represent the levels of statistical significance at 10%, 5%, and 1%, respectively.

The regression equation (5) is reanalyzed to validate robustness further using alternative stock illiquidity metrics. Specifically, the Amihud illiquidity measure from Equation (1) is substituted with Roll's impact illiquidity measure as detailed in Equation (2) or Zeros impact illiquidity measure as outlined in Equation (3). The outcomes presented in Table 7 reveal that investor sentiment consistently exerts a significantly negative effect on stock illiquidity, affirming that the primary conclusion remains valid across two alternative illiquidity measures.

Table 7. Alternative illiquidity measures

	(1)	(2)	(3)	(4)
	Roll	*Roll*	*Zeros*	*Zeros*
Senti	–0.005***	–0.006***	–0.005***	–0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
Lev	0.000***	0.000***	0.000**	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
RevGrow	–0.000***	0.000***	–0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
FirmSize	–0.000***	–0.001***	–0.000***	–0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
InstOwn	0.000	0.000***	–0.001***	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
BM	0.002***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
ROA	0.001***	–0.000	–0.001**	–0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Volatility	–0.020***	–0.034***	–0.035***	–0.061***
	(0.001)	(0.001)	(0.001)	(0.002)
Constant	0.014***	0.017***	0.010***	0.015***
	(0.000)	(0.001)	(0.001)	(0.001)
Firm FE	No	Yes	No	Yes
Year FE	No	Yes	No	Yes
Observations	10,546	10,546	10,546	10,546
R-squared	0.495	0.559	0.268	0.330

Note: The table presents the results from regression analysis on alternative measures of stock illiquidity, specifically Roll's impact and Zeros impact, in relation to investor sentiment and various control variables. Robust standard errors are indicated in parentheses below the estimated coefficient of each variable. *, **, and *** represent the levels of statistical significance at 10%, 5%, and 1%, respectively.

Additionally, the change in stock illiquidity is regressed against the change in investor sentiment:

$$\begin{aligned}\Delta Illiq_{i,t} &= \beta_0 + \beta_1 \Delta Senti_{i,t} + \beta_2 Lev_{i,t} \\ &+ \beta_3 RevGrow_{i,t} + \beta_4 FirmSize_{i,t} \\ &+ \beta_5 InstOwn_{i,t} + \beta_6 BM_{i,t} + \beta_7 ROA_{i,t} \\ &+ \beta_8 Volatility_{i,t} + FirmFE + YearFE + \varepsilon_{i,t},\end{aligned} \tag{8}$$

where $\Delta Illiq$ represents the change in $Illiq$ from t-1 to t, and $\Delta Senti$ denotes the change in $Senti$ from t-1 to t. As presented in Table 8, the regression coefficient for $\Delta Senti$ is negative and significant at the 1% level. This indicates that an escalation in investor sentiment is linked to a decline in stock illiquidity (enhanced liquidity). Such results are consistent with the initial findings.

Table 8. Changes in illiquidity and sentiment

	(1)	(2)
	ΔIlliq	*ΔIlliq*
ΔSenti	–0.541***	–0.865***
	(0.072)	(0.082)
Lev	0.001	0.015**
	(0.003)	(0.006)

Table 8 (cont.). Changes in illiquidity and sentiment

	(1)	(2)
	ΔIlliq	***ΔIlliq***
RevGrow	–0.008***	–0.007***
	(0.002)	(0.002)
FirmSize	–0.003***	–0.010***
	(0.000)	(0.002)
InstOwn	0.006	0.002
	(0.006)	(0.008)
BM	0.028***	0.023***
	(0.002)	(0.004)
ROA	–0.040***	–0.084***
	(0.013)	(0.019)
Volatility	–0.603***	–1.548***
	(0.050)	(0.112)
Constant	0.056***	0.256***
	(0.010)	(0.035)
Firm FE	No	Yes
Year FE	No	Yes
Observations	7,234	7,234
R-squared	0.089	0.417

Note: The table displays the outcomes of regression analysis concerning the changes in stock illiquidity relative to changes in investor sentiment and various control variables. Robust standard errors are indicated in parentheses below the estimated coefficient of each variable. *, **, and *** represent the levels of statistical significance at 10%, 5%, and 1%, respectively.

Finally, the inverse correlation between stock illiquidity and investor sentiment raises questions regarding causality. Stocks with elevated investor sentiment might exhibit increased liquidity. Conversely, stocks with high liquidity could attract investors, generating heightened investor sentiments. To distinguish causal pathways, this research strategically adopts one-year-lead stock illiquidity as the dependent variable to echo the baseline findings, as delineated by the subsequent equation:

$$\begin{aligned} Illiq_{i,t+1} &= \beta_0 + \beta_1 Senti_{i,t} + \beta_2 Lev_{i,t} \\ &+ \beta_3 RevGrow_{i,t} + \beta_4 FirmSize_{i,t} \\ &+ \beta_5 InstOwn_{i,t} + \beta_6 BM_{i,t} + \beta_7 ROA_{i,t} \\ &+ \beta_8 Volatility_{i,t} + FirmFE + YearFE + \varepsilon_{i,t}. \end{aligned} \tag{9}$$

Consistent with expectations, the outcomes presented in Table 9 reveal that investor sentiment exerts a significantly negative influence on future stock illiquidity. This result supports the hypothesis that elevated investor sentiment adversely impacts stock illiquidity rather than the reverse.

Table 9. Lead illiquidity measure

	(1)	(2)
	Illiq$_{t+1}$	***Illiq$_{t+1}$***
Senti	–0.767***	–0.283***
	(0.050)	(0.054)
Lev	0.018***	0.005
	(0.003)	(0.006)
RevGrow	0.001	–0.004***
	(0.001)	(0.002)
FirmSize	–0.024***	–0.026***
	(0.001)	(0.002)
InstOwn	–0.020***	–0.012**
	(0.004)	(0.006)
BM	0.060***	0.062***
	(0.002)	(0.004)
ROA	0.019	–0.031*
	(0.012)	(0.017)
Volatility	–1.016***	–0.612***
	(0.043)	(0.086)
Constant	1.096***	0.821***
	(0.035)	(0.049)
Firm FE	No	Yes
Year FE	No	Yes
Observations	7,234	7,234
R-squared	0.446	0.465

Note: The table presents the results from regression analysis of one-year-lead stock illiquidity on investor sentiment and various control variables. Robust standard errors are indicated in parentheses below the estimated coefficient of each variable. *, **, and *** represent the levels of statistical significance at 10%, 5%, and 1%, respectively.

4. DISCUSSION

The findings from baseline regressions presented in Table 3 demonstrate a significant positive relationship between investor sentiment and stock liquidity within the Chinese context, thereby supporting Hypothesis 1. Positive investor sentiment is associated with increased stock purchases, aligning with the discoveries of Odean (1998), Asem et al. (2016), and various scholars. Odean (1998) developed a theoretical framework illustrating that overconfident investors tend to engage in more trading activities, enhancing market liquidity. Likewise, Asem et al. (2016) explored the dynamics between market illiquidity and the discount on seasoned equity offering (SEO) prices in the Australian market, revealing that during periods of negative investor sentiment, there is a greater demand for SEO price concessions among less liquid companies compared to their more liquid counterparts. This indicates that a firm's liquidity concerns intensify as investor sentiment deterio-

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rates. Nonetheless, these findings contradict the hypothesis posited by a minority of studies. For instance, Dunham and Garcia (2021) identified a negative correlation between investor sentiment, as measured by Twitter, and liquidity; improved sentiment correlated with reduced liquidity. This discrepancy may be attributed to the unique characteristics of Twitter-based investors, who may possess distinct market perceptions. The predominant evidence suggests a positive linkage between investor sentiment and stock liquidity.

The results in Table 4 reveal an inverse U-shaped relationship between investor sentiment and stock liquidity, which merits thorough elucidation. Initially, as investor sentiment enhances, confidence in the market escalates, leading to increased trading activity and, thus, heightened liquidity. This phase reflects the positive influence of optimistic sentiment, facilitating smoother transactions and greater market efficiency. However, beyond a critical sentiment threshold, the relationship inverts, evidencing a diminution in liquidity. This inflection point can be attributed to overoptimism, where excessive speculative trading and inflated asset valuations deter informed trading, thereby increasing the cost of liquidity and reducing its availability. Such a scenario underscores the complexity of sentiment's impact on market dynamics, where extreme sentiment transitions from beneficial to detrimental for market liquidity. This nuanced relationship highlights the dual-faceted role of investor sentiment in shaping market behavior, emphasizing the necessity for a balanced sentiment spectrum to sustain optimal liquidity levels.

Table 5 employs interaction terms to assess the moderating effects of control variables on the relationship between investor sentiment and stock illiquidity. Nearly all variables exacerbate the adverse effect of investor sentiment on stock illiquidity, except the book-to-market ratio. In instances of elevated leverage, rapid revenue growth, and significant stock volatility, firms may encounter heightened uncertainty, and exhibit increased sensitivity to investor sentiment. Consequently, an escalation in investor sentiment amplifies its negative (positive) effect on stock illiquidity (liquidity). Larger enterprises or those with a substantial proportion of institutional investors tend to garner more investor attention, rendering them more responsive to shifts in investor sentiment. For growth-oriented firms characterized by a low book-to-market ratio, the projections of their future cash flows are more susceptible to investor expectations, thereby heightening their sensitivity to investor sentiment. The observed moderating effects are logical and align with theoretical anticipations.

Table 8 delineates the association between investor sentiment fluctuations and stock illiquidity alterations. The analysis demonstrates that a surge in investor sentiment (reflecting a more positive emotional disposition among investors) is inversely related to an enhancement in stock illiquidity. Specifically, an elevation in investor sentiment precipitates an augmentation in stock liquidity. These outcomes align with Hypothesis 1, positing that investor sentiment positively influences stock liquidity.

Table 9 exhibits that the nexus between investor sentiment and subsequent illiquidity levels remains negative. This result harmonizes with the findings of Liu (2015) and Debata et al. (2018). Liu (2015) ascertains, through Granger causality tests, that investor sentiment Granger-causes market liquidity. Debata et al. (2018) discovered that the level of stock illiquidity is inversely associated with prior investor sentiment. These outcomes suggest that investor sentiment precipitates alterations in liquidity levels rather than stock liquidity influencing investor sentiment.

CONCLUSION

This study investigates the influence of investor sentiment on stock illiquidity among publicly listed firms in China from 2010 to 2019. The analysis employs both univariate and multivariate ordinary least squares and fixed-effects regressions. Across all regression models, investor sentiment consistently demonstrates a significant negative (positive) effect on stock illiquidity (liquidity). Moreover, the study reveals that the nexus between investor sentiment and stock illiquidity follows a convex, U-shaped pattern. Elevated investor sentiment lessens its negative impact on stock illiquidity. Examination of interaction terms with control variables indicates that the adverse effect of investor sentiment on stock illiquidity is more marked in cases of high leverage, robust revenue growth, substantial firm size, significant institutional ownership, intense stock volatility, and lower book-to-market ratios. The baseline findings are validated across three submarkets, with two alternate measures of illiquidity, and in the context of changes in sentiment and illiquidity. Causality analysis utilizing one-year-lead illiquidity reinforces the directional influence from investor sentiment to stock illiquidity rather than the converse.

While this study offers valuable insights into the relationship between investor sentiment and stock illiquidity in China, it does present certain limitations that open avenues for future research. Firstly, the study's broad focus encompasses many firms across different sectors and submarkets. Future research could benefit from a more granular approach, examining specific industries to understand the nuances of this relationship in different market segments. Secondly, the study period does not include significant market events, such as the COVID-19 pandemic, which could profoundly impact investor sentiment and stock liquidity. Subsequent research could explore how extraordinary events alter the dynamics of investor sentiment and stock liquidity, providing insights into market behavior under stress. Furthermore, the study primarily relies on regression analysis; future work could incorporate more advanced econometric models to capture complex interactions and nonlinearities. Lastly, exploring cross-market comparisons, particularly with markets outside of China, could offer a broader perspective on the universality or specificity of these findings.

AUTHOR CONTRIBUTIONS

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Funding acquisition: Chunxiao Xue, Jianing Zhang.
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