Sentiment Divergence and its Impact on Share Liquidity

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This study examines the impact of divergent investor sentiment derived from tweets and news media content on a firm's share liquidity. This study analyzes a sample of 1,945 publicly traded U.S. firms from January 2015 to April 2021. Utilizing the daily Amihud illiquidity measure, bid-ask spread, and share turnover as liquidity proxies, the results reveal a positive relationship between divergent sentiment and share liquidity. Interestingly, this effect was more pronounced during the COVID-19 pandemic period. Moreover, mixed evidence shows that the effect of divergent sentiment on share liquidity increases during periods of increased investor attention. This study contributes to our understanding of how investor sentiment influences financial markets by highlighting the role of sentiment divergence in shaping share liquidity.

Keywords: Behavioral Finance; Disagreement; Sentiment; Stock Liquidity

JEL Classification: G12; G30; G40.

I. Introduction

The impact of investor disagreement on share prices and trading volume is well documented in the finance literature.[1] In fact, aside from trading induced by changes in financial circumstances or needs (e.g., inheritance,

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1. E.g., Banerjee and Kremer (2010); Carlin et al. (2014); Chang et al., 2015.

(*Multinational Finance Journal*, 2024, vol. 28, no. 1/2, pp. 3-39)

https://doi.org/10.5281/zenodo.14957129

paying taxes, buying a house), it is difficult to understand why investors would otherwise trade if they did not have differing opinions. However, despite the importance of investor disagreement in financial markets, there is still a lack of understanding of the factors that contribute to diverse investor perspectives, especially as information complexity increases.

The increasing amount of information available from multiple media sources, such as traditional news articles and user-generated content on social media platforms, has led to the proliferation of sentiment signals in financial markets, which market participants then use to inform their decisions. For example, prior studies have established a connection between investor sentiment derived from media content and a firm's share liquidity (Cookson and Niessner, 2020; Dunham and Garcia, 2020; Liu, 2015) and sentiment disagreement between social media and news media content has been found to be related to abnormal trading volume (Giannini et al., 2019).

Despite the importance of investor disagreement, the impact of divergence in sentiment from different media sources on a firm's share liquidity has received little attention in previous research. This study addresses this gap by examining the relationship between the divergence in investor sentiment derived from tweets and traditional news media content and share liquidity.

Several proxies have been employed to measure the divergence of opinions, including the volatility of buy versus sell opinions from online message boards (e.g., Antweiler and Frank, 2004; Giannini et al., 2019), trading activity, as reflected in the magnitude of retail investor stock trading (Barber and Odean, 2001), and analysts' earnings forecast dispersion (Diether et al., 2002). However, the impact of the divergence in sentiment from different media sources on a firm's share liquidity remains unclear.

Theoretical models offer valuable insights into how divergent sentiments can affect liquidity. Information aggregation models suggest that dispersed information is incorporated into prices through informed investor trading (Grossman and Stiglitz, 1980; Hellwig, 1980). If sentiment divergence indicates diverse private information, it could lead to increased trading volume and liquidity. Speculative trading models propose that variances in investor interpretations of signals drive trading as investors chase profits based on diverse valuations (Harris and Raviv, 1993; Varian, 1989). Behavioral models connect biases, such as overconfidence, to elevated trading (Odean, 1998), potentially signaled by sentiment divergence. Additionally, models of confirmation bias suggest that investors focus on signals that align with their perspectives (Rabin and Schrag, 1999), a behavior that is possibly reflected in sentiment divergence. Taken together, these models suggest that sentiment divergence can enhance liquidity by acting as a proxy for mechanisms such as information asymmetry, disagreement, and behavioral biases. However, empirical examinations of this relationship are sparse.

Recent studies reveal a positive relationship between investor disagreement and asset returns (Banerjee and Kremer, 2010; Carlin et al., 2014), suggesting that heterogeneous priors can amplify disagreement in financial markets. Empirical studies have linked divergent sentiment with market activity, associating disagreement observed in online forums with trading volume (Antweiler and Frank, 2004; Sprenger et al., 2014) and sentiment with liquidity (Bollen et al., 2011; Dunham and Garcia, 2020; Garcia, 2013). Nevertheless, the explicit impact of sentiment divergence across various media sources, such as tweets and traditional news, on share liquidity remains largely unexplored.

This study bridges this gap by empirically examining the relationship between sentiment divergence sourced from these media sources and share liquidity. Moreover, economic theory suggests a positive relationship between liquidity and sentiment disagreement from media sources. Private signals, such as sentiment from tweets within a user's network, might differ from public sentiment signals conveyed by traditional news articles. This divergence may originate from disagreements over asset prices, a topic that has not been thoroughly studied in previous research. This study aims to address this gap in the literature.

This study examines the relationship between the divergence of daily tweet and news sentiment at the firm level and its effect on a firm's share liquidity. Using ordinary least squares regression models, I analyzed a sample of 1,945 publicly traded U.S. corporations from January 2015 to April 2021. The primary liquidity measure is a firm's daily Amihud illiquidity measure (Amihud, 2002), a widely accepted liquidity metric. To ensure the robustness of the study, additional liquidity proxies were incorporated into the analysis, including the firm's daily share bid-ask spread and share turnover. By expanding the research timeframe and utilizing Twitter data, which reflect a more diverse user base, this study broadens the scope of earlier investigations.

The primary conclusions drawn from this study include several key findings. First, there is a positive relationship between divergent sentiment and share liquidity. Notably, a one standard deviation change in the lagged divergent sentiment measures results in a 10.41% change in the median Amihud illiquidity measure. Second, the positive nominal impact of divergent sentiment on share liquidity manifested with increased potency during the COVID-19 pandemic period. However, it is crucial to note that this was primarily attributable to elevated levels of share illiquidity during that time. Finally, the evidence is mixed with regard to the proposition that the effect of divergent sentiment on share liquidity becomes more pronounced during periods of elevated investor attention.

These findings indicate that the divergence between daily tweet sentiment and news sentiment at the firm level, representing a dimension of asset value disagreement, significantly impacts a firm's share liquidity. This research builds on and expands the findings of Giannini et al. (2019), who explore investor sentiment using data from StockTwits and news articles. However, this study covers a broader timeframe, including the COVID-19 pandemic, uses Twitter data (representing a broader user base than StockTwits), focuses specifically on share liquidity rather than abnormal trading volume, and employs novel Bloomberg sentiment data.

This study substantially contributes to the literature on liquidity and investor behavior by identifying divergent investor sentiment as a factor that influences share liquidity. Furthermore, it provides evidence of divergent investor sentiment's impact on share liquidity, thereby enhancing our understanding of how investor sentiment affects financial markets. This study illuminates the relationship between share liquidity and divergent investor sentiment, filling a gap in the literature between these two research areas.

The remainder of this paper is organized as follows: Section 2 reviews the relevant literature and develops the hypotheses; Section 3 discusses the data and methodology; Section 4 presents the empirical results; and Section 5 concludes the paper.

II. Related Literature and Hypothesis Development

A. *Review of Literature on Disagreement*

Theoretical models of disagreement have been extensively studied, shedding light on the complex interaction between private information, personal interpretation of public signals, and behavioral biases, culminating in rational investors crafting distinct perspectives on stock prices (Kruger, 2020; Hong and Stein, 2007). This foundational research has its roots in pioneering works, especially that of Varian (1989), who examined the differences of opinion in financial markets, laying the groundwork for understanding the implications of disagreement in risk assessment. Behavioral finance models also examine the role of sentiment in driving trading and price. Barberis et al. (1998) develop a model showing how investor sentiment affects asset valuations and earned returns. Their model predicted that sentiment-driven mispricing could diverge from fundamentals in the short run, but correct in the long run. This is related to disagreement models, as sentiment differences can cause varied subjective valuations.

Such a divergence in viewpoints was found to fuel stock trading and enhance liquidity. Within this framework, Banerjee and Kremer (2010) state that persistent disagreement is often rooted in fluctuating initial beliefs among investors, influenced by the unending flow of information within financial markets. This has led investors to constantly revise their beliefs and opinions. Building on this, Harris and Raviv (1993) further expounded that differences of opinion significantly contribute to trading activity, metaphorically stating that "differences in opinion make a horse race," giving a profound insight into the role of disagreement in trading dynamics.

A wealth of research supports these theoretical models, accentuating the role of disagreement on various facets of stock trading. For instance, Goldstein and Yang (2015) suggest that diverse information significantly augments the informativeness of asset prices, whereas Baker and Stein (2004) and Kyle et al. (2018) underscore how heightened disagreement actively fosters stock trading. This relationship was further examined by Cookson and Niessner (2020), who explored the interplay between varying sentiments conveyed through tweets and traditional media, illustrating how such disparities in information sets contribute to increased trading.

Focusing on specific divergences in sentiment, the genesis of investor disagreement is subject to scrutiny. Private information is recognized as the primary catalyst, with differing investment philosophies playing a secondary yet significant role (Cookson and Niessner, 2020; Hong and Stein, 2007). The exploration further extends to modern communication channels such as social media. Cookson and Niessner (2020) leveraged StockTwits data to demonstrate that disparities in user information led to more trading than mere differences in investment philosophies. Furthermore, Hong and Page (2004) discovered that diversified viewpoints expressed via tweets are more informative than the uniform perspectives of a less diverse and skilled group. This compelling evidence underscores the role of the sentiment variance between tweets and traditional media in identifying divergent information sets, thereby directly influencing investor disagreement and shaping share liquidity.

B. Review of Literature on Media Coverage and Behavioral Biases

The role of traditional and social media in shaping investor sentiment and trading behavior has been a growing area of research. Although still significant in reporting information, traditional news sources have seen social media rise to the forefront in the dissemination process, substantially influencing public perception and driving the spread of news and ideas (Nikkenen and Peltomaki, 2020; Bartov et al., 2018). Studies have consistently indicated that sentiment expressed on social media can significantly impact a company's financial performance parameters, such as stock returns, liquidity, financial distress, and analysts' earnings ratings (Bollen et al., 2011; Bartov et al., 2018; Chen et al., 2014; Dunham and Garcia, 2020; Dunham and Garcia, 2021; Garcia, 2021; Garcia, 2022; Gu and Kurov, 2020).

In this context, Pedersen (2022) and Cookson et al. (2023) shed light on the influence of news and Twitter content on molding investor perceptions, potentially leading to heightened trading activity. It is worth noting that qualitative information gleaned from various media sources played a crucial role in financial markets. Evidence has revealed that textual data from market professionals and firm disclosures can predict stock returns (Jegadeesh and Wu, 2013; Loughran and McDonald, 2016). Furthermore, sentiment derived from news articles has predictive power for stock returns and share liquidity (Garcia, 2013; Tetlock, 2007; Tetlock et al., 2008; Dunham and Garcia, 2020). Indeed, tweets convey new information, and their sentiments can have varying effects on share liquidity compared to traditional news articles (Bartov et al., 2018; Dunham and Garcia, 2020; Halim et al., 2019).

These relationships are further complicated by the interplay between behavioral biases. Such biases interact heavily with media sentiment to influence trading volumes and liquidity. Overconfidence, for instance, can result in excessive trading and asset price bubbles (Scheinkman and Xiong, 2003; Kelley and Tetlock, 2013). High returns can augment overconfidence and stimulate trading activity, particularly for smaller stocks (Statman et al., 2006). Moreover, investor sentiment can affect noise trading and liquidity either directly or indirectly, potentially causing a divergence of prices from intrinsic values or an increase in irrational market makers (Kyle, 1985; De Long et al., 1990; Baker and Stein, 2004). These effects underscore the intricate interplay between media sentiment and behavioral biases, as seen in the contrasting impacts of sentiment from tweets on share liquidity and price informativeness (Liu, 2015; Dunham and Garcia, 2020; Han and Yang, 2013).

The literature highlights the intricate relationships among traditional media, social media, investor sentiment, and trading behavior. Evidence suggests that qualitative information conveyed via tweets and traditional news media affects stock returns and liquidity in different ways. The divergence in firm-level sentiment derived from these sources reflects the diversity of qualitative information and potentially serves as a proxy for disagreement between users generating tweets and news outlets reporting traditional news. This leads to the following hypothesis.

Hypothesis 1: The divergence in firm-level sentiment derived from tweets versus news articles is positively related to the share liquidity.

The impact of pandemic-induced anxiety, especially as reflected in news content, corroborates Glosten and Milgrom's (1985) economic theory, which suggests that share liquidity tends to rise in situations marked by uncertainty and risk. Recent research, including studies by Ortmann, Pelster and Wengerek (2020), demonstrates that the COVID-19 pandemic led to a marked increase in trading volume. In light of these findings, I hypothesize that the pandemic period would amplify the impact of divergent sentiment on share liquidity.

Hypothesis 2: The effect of divergent firm-level sentiment derived from tweets versus news articles on share liquidity was more potent during the COVID 19 pandemic period.

Building on the above discussion, this study's findings enrich our understanding of the unique impacts of social media versus traditional media sentiment on financial markets. The results confirm prior observations on the capacity of qualitative signals to shape trading behavior. Specifically, the results highlight the significant influence of divergent media sentiment on financial markets by establishing a link between divergent sentiment derived from tweets and news media content and share liquidity.

III. Methodology and Data

A. Methodology

Pooled regression models [2] were used to examine the effect of the divergence between sentiments derived from tweets and news articles, and share liquidity. Errors were corrected for autocorrelation and heteroskedasticity using a Newey and West (1987) correction with seven lags.[3] The primary regression specification is outlined in equation (1).

$$\mathrm{Liq}_{i,t} = B_0 + \sum_{k=1}^{k=5} B_k\, \mathit{DivergentSent}_{i,t-k} + B\, X_{i,t-1} + \varepsilon_{i,t} \qquad (1)$$

In this equation, $\mathrm{Liq}_{i,t}$ is a firm's share liquidity measure for firm i at time t; the variable of interest, $\mathrm{DivergentSent}_{i,t-1}$, represents the absolute value of the daily sentiment derived from tweets less the sentiment derived from news articles for firm i at time $t-1$; and $X_{i,t-1}$ is a vector of firm characteristic control variables for firm i at time $t-1$. The regressions also control for industry and year-quarter fixed effects.

Emotional responses to events are typically more time-sensitive than cognitive evaluations are, and there is often a lag between the two

2. The panel dataset is unbalanced due to some firms' inconsistent production of daily tweets or news content. Wooldridge (2010) recommends using pooled OLS when varying samples are needed for different periods.

3. According to Newey and West (1994), the optimal number of lags (L) to use in a firm-level sample can be calculated by taking the floor of $\frac{4\left(\frac{N}{100}\right)^2}{9}$, where N is the sample size. In this case, the maximum number of quarterly observations per firm is 1,632; thus, the optimal number of lags is 7.

types of responses, with the emotional response usually lagging the cognitive response (Loewenstein et al., 2001). Several studies also suggest that sentiment can influence company performance, albeit with delay. For example, Dunham and Garcia (2020) find that news and Twitter sentiment can affect share liquidity with a five-day lag, Ferguson et al. (2015) document that five-day lagged sentiment affects share returns, and Bollen et al. (2011) show that Twitter sentiment can predict share returns with up to a six-day delay. Hence, this study employs a five-day lag structure to account for persistence when measuring sentiment.

B. Dependent Variable

This study uses the Amihud illiquidity measure (Amihud, 2002), founded on Kyle's (1985) illiquidity model, to measure share liquidity. This measure is computed for firm i on trading day t as follows:

$$Amihud_{i,t} = \frac{10^6 * |\text{Return}_t|}{\text{Price}_t * \text{Volume}_t} \tag{2}$$

This measure calculates the expected price impact of a trade by examining the relationship between the absolute returns and trading volume. A higher Amihud measure denotes greater illiquidity, whereas a lower measure indicates lower illiquidity. A square-root transformation was used to alleviate potential statistical distortions owing to the right-skewed distribution of the Amihud measure.

Two additional liquidity measures were employed to ensure robustness. First, the daily average of all bid-ask spreads (BAS) as a percentage of the firm's mid-price is used as a measure of share liquidity. The BAS reflects the maximum round-trip trading costs for investors and is influenced by inventory holding costs, order processing fees, and adverse selection costs (Lee and Chung, 2018), where a higher BAS indicates decreased liquidity. The BAS has been widely used in previous studies to measure liquidity (e.g., Chung et al., 2010; Chung and Zhang, 2014; Demsetz, 1968; Dunham and Garcia, 2020; Fong et al., 2017). To reduce the impact of extreme outliers, BAS was winsorized at the 99 % level.

Second, the share turnover ratio, measured as the number of shares traded on a firm on the current day divided by the total current number of shares outstanding, is used as a liquidity proxy. Share turnover measures the frequency at which a firm's shares are bought and sold, providing insight into the firm's liquidity, and has been widely used in previous research to measure liquidity (e.g., Brennan et al., 1998); Datar and Radcliffe, 1998).

C. Sentiment Measures

In line with prior studies that use Bloomberg sentiment measures as proxies for firmlevel investor sentiment (e.g., Behrendt and Schmidt, 2018; Garcia, 2022; Gu and Kurov, 2020), this study use firm-level Bloomberg's daily sentiment measures from Twitter and news media to calculate divergent sentiment, which is computed as the absolute difference between tweet sentiment and news sentiment. For most firms, Bloomberg estimates an investment sentiment based on firm-specific news stories and another based on investor sentiment generated from firm-specific tweets. Bloomberg calculates a sentiment polarity score for each firm-specific news story and tweet and then combines the sentiment scores of the individual articles and tweets into daily sentiment scores for news and tweets. Additionally, a dummy variable was included and set to 1 when Twitter sentiment was greater than news sentiment, indicating a positive divergence between Twitter sentiment and news sentiment. Bloomberg also reports each firm's total number of news stories and tweets. Daily news and tweet counts were included in the regressions, as they could also affect the firm's information environment and serve as proxies for investor attention.

Market-level sentiment affects share liquidity (Liu, 2015). To account for daily market sentiment, two daily market sentiment measures were included in the regressions as controls: the Economic News Sentiment (ENS) index (Shapiro et al., 2020), which assesses the sentiment conveyed in economic news articles, and the Chicago Board Options Exchange Volatility Index (VIX), commonly known as the "investor fear gauge" (Whaley, 2000).

D. Firm-level and Market Controls

Previous research has shown a link between bid-ask spreads and firm-specific characteristics associated with information asymmetry (Bollen et al., 2004; Chordia et al., 2000, 2001; Llorente et al., 2002). These characteristics include firm size, as measured by the logarithm of market capitalization; firm risk, as measured by a firm's beta; share price volatility, as measured by the log of the daily share price trading range over the prior day's share closing price; daily share turnover, calculated as the daily trading volume scaled by shares outstanding; the inverse of the current share price; and recent share returns (Chorida et al., 2001; Hasbrouck and Seppi, 2001)[4]. In the regression analyses, I utilized the logged and winsorized versions of these variables to improve the statistical properties and reduce the influence of outliers. In addition, investor attention can affect liquidity. Therefore, consistent with Bali et al. (2021), I include the total number of analysts covering a firm as a proxy for investor attention. Higher levels of analyst coverage reduce information asymmetry (e.g., Bowen et al., 2008), reduce adverse selection costs for liquidity providers, and improve liquidity.

E. Sample Selection and Summary Statistic

The sample consists of 1,945 publicly listed U.S. companies, with 174, 232 firm-day observations from January 2015 to April 2021, based on the availability of Bloomberg news and Twitter sentiment data. Descriptive statistics for the liquidity and control variables, as well as the sentiment divergence measure and counts for daily tweets and news stories are provided in Table 1.

Panel A shows that the median and mean Amihud illiquidity measures are 0.0001 and 0.0037, respectively, indicating a right skew. Further, the median and mean bid-ask-spread are 0.0397% and 0.0770%, respectively, and the median and mean share turnover are 0.0020 and 0.0032, respectively. Panel A also shows that the median sample firm has a market capitalization of 39.06 billion, 24 analysts covering the firm, and a beta of 1.0776. Panel B shows that the median and mean divergent sentiment are 0.1344 and 0.2197, respectively, with 62.7% of the daily observations in the sample having a news sentiment that is higher than Twitter sentiment, 35.5% having Twitter sentiment that is higher than news sentiment, and 1.8% having the same Twitter and news sentiment measure. Panel B also shows that the median sample firm generates

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4. To mitigate the effect of extreme outliers, the beta and five-day average return were winsorized at the 0.5% and 99.5% level.

TABLE 1. Descriptive Statistics

Panel A: Liquidity and control variables

	Minimum	**Maximum**	**Median**	**Mean**	**Std. Dev.**
Amihud Illiquidity	.0000	1.7580	.0001	.0037	.0496
Bid-Ask Spread (%)	.0054	5.1282	.0397	.0770	.1407
Share Turnover	.0000	.0157	.0020	.0032	.0032
|Five-Day Avg Return (%)|	.0000	4.2035	.5050	.8193	.9096
Total Analysts	0	58	24	24.2406	10.2240
Share Price Volatility	.0002	2.9718	.0206	.0298	.0356
Beta	-.0614	2.8727	1.0776	1.0861	.3360
Market Capitalization ($Millions)	4,260.8	2,408,418.3	39,060.7	98,640.8	177,062.8
1 / Share Price	.0002	12.1065	.0155	.0343	.1345
VIX	9.1400	82.6900	15.6300	19.0828	10.3963
Economic News Sentiment	-.6453	.3029	.0235	-.0226	.2169
Sample Characteristics					
Number of Firms	1,945				
Observations	174,232				

Panel B: Sentiment Data

	Minimum	Maximum	Median	Mean	Std. Dev.	Negative	Zero	Positive
Divergent Sentiment(|*Twitter-News*|)	0.0000	1.9023	0.1344	0.2197	0.2327	109,285	3,197	61,750
Divergent Sentiment Ratio	0.0000	6.3929	0.1245	0.2559	0.6102			
Twitter Sentiment	-0.9980	0.9970	0.0040	0.2114	0.1578			
News Sentiment	-1.0000	1.0000	0.0526	0.1137	0.3024			
Daily Tweets Count	0	138,934	46.000	304.880	1,295.771			
Daily News stories Count	0	6,245	15.000	43.387	95.752			

Panel C: Transformed Variables

	Minimum	Maximum	Median	Mean	Std. Dev.
$\sqrt{}$Amihud Illiquidity	0.0000	1.3260	0.0106	0.0218	0.0566
$\log(\text{Share Turnover} + 0.0002)$	-8.4890	-4.1387	-6.1125	-6.0010	0.7616
$\log(\text{Total Analysts} + 1)$	0.0000	4.0775	3.2189	3.1179	0.5311
$\log(\text{Share Price Volatility} + 0.0002)$	1.4495	14.6945	10.5729	10.3910	1.7232
$\log(\text{Market Capitalization})$	0.0000	11.8418	3.8501	3.5074	2.3468
$\log(\text{Daily Tweets Count} + 1)$	-7.9108	1.0892	-3.8722	-3.7995	0.7028
$\log(\text{Daily News Stories Count} + 1)$	0.0000	8.7397	2.7726	2.5341	1.7311

Note: Table 1 reports descriptive statistics on the sentiment and firm-specific variables control variables for the sample firms over the January 2015 – April 2021 period. All data are daily and taken from Bloomberg. Panel A includes descriptive statistics for the liquidity and control variables, and Panel B summarizes the sentiment disagreement measure and counts for daily tweets and news stories. Panel C summarizes the transformed variables used in the regressions. A complete list and description of the variables used in the study can be found in Appendix 1.

46 tweets per day and 15 news stories, although these values vary significantly among firms in the sample. Panel C presents the summary statistics for the transformed variables used in the regression analyses.

Moreover, the divergent sentiment measure exhibits a relatively low correlation with the control variables, varying from -0.15 with daily VIX to 0.14 with daily economic news sentiment. Notably, the counts of tweets and news stories correlate negatively with the Amihud measure at -0.01 and -0.03, respectively, indicating that news and tweet counts positively affect share liquidity. It is crucial to acknowledge that these relationships may undergo change when other factors are controlled for in a multivariate context. Additionally, there is a moderate positive correlation between the lagged divergent sentiment measures from t–1 to t–5, ranging from 0.18 between t–2 and t–4 to 0.44 for t–4 and t–5.

Table 2 presents the Pearson correlations between the divergent sentiment measure and the control variables. In line with the hypothesis of a positive effect of divergent sentiment on share liquidity, divergent sentiment demonstrates a negative correlation with the Amihud measure (-0.02) and the bid-ask spread (-0.03), while showing a positive correlation with share turnover (0.01).

IV. Empirical results

A. Primary Results

Table 3 presents the results of a pooled regression analysis examining the relationship between divergent sentiment derived from Twitter and news media content and share liquidity for all sample firms. Consistent with prior research (e.g., Brennan et al., 2013; Chordia et al., 2009), the dependent variable in columns 1–2 is the square root of the Amihud illiquidity measure for firm i, measured at time t. Column 3 uses the bid-ask spread taken as a percentage of the mid-price, whereas column 4 employs the logarithm of share turnover. The control variables lagged at t-1 and include the absolute value of the five-day average share return, number of analysts covering the firm, daily share price volatility , beta, market capitalization, the inverse of the share price, share turnover, VIX, and economic news sentiment. The variable of interest, divergent sentiment, also lags at time t-1. In addition, all regressions include quarter and industry fixed effects.

TABLE 2. Correlation Matrix

	Amihud (t+1)	1	2	3	4	5	6	7	8	9	10	11	12
1 BAS Pct (t+1)	0.5500***												
2 Divergent Sentiment	-0.0200***	0.0300***											
3 Share Turnover	0.0100***	0.1800***	0.0600***										
4 Tweets Count	-0.0100***	0.0300***	0.0100***	0.0900***									
5 News Stories Count	-0.0300***	0.1000***	0.0400***	0.0100***	0.5900***								
6 —Five-Day Return—	0.1200***	0.3200***	0.0300***	0.4900***	0.0300***	-0.0200***							
7 Total Analysts	-0.1300***	0.3600***	0.0100***	0.1300***	0.2000***	0.3200***	0.2000***						
8 Daily Price Volatility	0.1600***	0.4000***	0.0000*	0.5100***	0.0800***	-0.0300***	0.5200***	-0.2000***					
9 Beta	0.0400***	0.1300***	0.0000	0.2600***	0.0200***	0.0200***	0.2100***	0.0100***	0.2000***				
10 Market Cap.	-0.0400***	-0.1600***	-0.1000***	-0.2200***	0.2900***	0.4700***	-0.1600***	0.4200***	-0.1500***	-0.0700***			
11 Share Price Inverse	0.3800***	0.3900***	-0.0100***	0.1100***	-0.0200***	-0.0500***	0.1900***	-0.1600***	0.2500***	0.1500***	-0.0900***		
12 VIX	0.0700***	0.2700***	-0.1500***	0.2300***	-0.0500***	0.0700***	0.3900***	-0.1000***	0.5100***	-0.0100***	-0.0300***	0.0800***	
13 Economic News Sent.	-0.0400***	0.1400***	0.1400***	-0.1400***	0.0500***	0.0500***	-0.2300***	0.0800***	-0.2800***	0.0300***	-0.0200***	0.0500***	0.6700***

Note: Table 2 presents the Pearson correlation matrix of the variables used in the regressions. Appendix 1 provides a complete list and description of the variables used in this study. *** and ** denote significance at the 1% and 5% levels, respectively.

Column 1 of Table 3 presents the regression results for the Amihud measure against a set of control variables. The findings reveal that all control variables, excluding the firm's beta and the economic news sentiment measure, are statistically significant at the .01 level and show the expected signs. Specifically, the Amihud illiquidity measure negatively relates to the number of analysts covering the firm, the firm's market capitalization, and share turnover. Conversely, Amihud illiquidity shows a positive relationship with the inverse of share price, share price volatility, the inverse of daily price, VIX, and economic news sentiment.

Column 2 presents the regression results incorporating lagged control variables, divergent sentiment measures, and dummy variables, denoting that Twitter sentiment is greater than that of news media and the volume of news and tweets. These findings corroborate the hypothesis of a positive relationship between divergent sentiment and share liquidity. This is evidenced by all coefficients of the lagged divergent sentiment measures being statistically significant at the .01 level and displaying negative signs. The previously established control variables continue to show consistent signs and significance levels akin to the preliminary findings in column 1.

Moreover, these findings suggest that after controlling for variables impacting a firm's share liquidity, divergent sentiment inversely correlates with the Amihud illiquidity measure, indicating a positive relationship with liquidity. Intriguingly, the Twitter >news sentiment dummy variable at lag t–1 is negative and statistically significant at the .01 level, implying that liquidity improves when Twitter sentiment surpasses news sentiment. However, it is important to note that the magnitude of this effect is minimal.

Furthermore, the correlations shown in Table 2 suggest that when examined independently, the volume of tweets and news stories have an inverse relationship with share liquidity. However, in a multivariate context, column 2 reveals that an increase in news stories and tweets correlates with a decrease in liquidity. Boudoukh et al. (2018) provide a possible explanation that crucial firm-level information contributes to stock price volatility. This heightened volatility amplifies informational noise, escalates order-processing costs, and decreases share liquidity.

Interestingly, the influence of tweet volume on liquidity surpasses that of news story volume, and a t-test confirms this difference as statistically significant at the .01 level. Consistent with the results in column 2, Schmierback and Oeldorf-Hirsch (2012) assert that, compared to other media forms, tweets often lack reliability and sufficient verification, resulting in the spread of misleading tweets. All other things being equal, this could prompt a surge in misinformation, contribute to a more uncertain information environment, and consequently, reduce liquidity.

The results in column 2 exhibit the consistent effect of divergent sentiment on liquidity, as evidenced by the negative sign for all lagged divergent sentiment measures and the .01 significance level. This aligns with predictions from theoretical models of investor disagreement, particularly those suggested by Hong and Stein (2007), who argue that varied interpretations of public information result in disparate valuations among investors. This conclusion aligns with insights from prior studies, including those by Bollen et al. (2011) and Dunham and Garcia (2020).

Furthermore, these results are consistent with theoretical frameworks on how prices incorporate dispersed information in markets, such as influential models developed by Grossman and Stiglitz (1980) and Hellwig (1980). These models posit that the gathering of costly information provides a profit motive for informed trading. The evidence that divergent sentiment across Twitter and news content is positively associated with liquidity provides empirical support for the premise that heterogeneous information sets incentive-informed market participants to trade, thereby enhancing liquidity.

However, the results diverge from those of previous studies that hypothesize a negative association between differences in opinion and liquidity. For instance, the model developed by Holden and Subrahmanyam (1992) theoretically shows that disagreement can reduce liquidity under certain conditions related to risk aversion and short-sale constraints. In contrast, the findings demonstrate a robust positive relationship between sentiment divergence and liquidity. A potential reconciliation is that the model assumptions may not apply universally. Furthermore, our focus on divergent sentiment as a proxy for disagreement rather than direct opinion measures could explain the contrasting results.

Overall, the positive relationship between sentiment divergence and liquidity established in the present study conforms to the key theoretical predictions that investor disagreement arising from diverse interpretations of signals can increase trading volume and liquidity. Therefore, the findings validate fundamental financial theories on the role of heterogeneous beliefs in shaping market outcomes. By utilizing an indirect measure of sentiment divergence, this study offers a unique validation of the established frameworks, thereby enhancing our understanding of these crucial economic dynamics.

Moreover, the economic significance of the results is further underscored by the fact that a one standard deviation change in lagged divergent sentiment measures leads to a 10.41% change in the median Amihud illiquidity measure. Furthermore, including lagged measures of divergent sentiment improves the adjusted R2 and Akaike Information Criterion (AIC) compared to column 1. This is further supported by a Wald test, which demonstrates that the control model (column 1) is significantly inferior to the model with lagged divergent sentiment variables (column 2) ($X^2 = 709.48$, $p < .01$).

These findings also align with behavioral finance theories, such as those of Odean (1998), suggesting that overconfident traders may overestimate the value of their private information signals, leading to higher trading volumes when differences arise across investors. The results lend empirical support to the notion that sentiment divergence across information sources may represent overconfident differences in opinions stemming from cognitive biases.

Moreover, the positive relationship between sentiment divergence and liquidity provides empirical support for behavioral finance theories on the impact of confirmation bias on investors' beliefs and trading behavior. Rabin and Schrag (1999) suggest that confirmation bias leads individuals to improperly favor information that confirms their prior views. Sentiment divergence across Twitter and news could indicate a confirmation bias if investors selectively interpret signals from their preferred sources.

The results lend credence to established behavioral finance frameworks, proposing that cognitive biases can produce disagreement and heightened market activity, confirming models of overconfidence and confirmation bias. The robust link between divergent sentiment and liquidity demonstrates the impact of these cognitive biases on market behavior.

The results in column 2 of Table 3 reveal a positive relationship between divergent sentiment conveyed through tweets and news media content and share liquidity. To confirm the robustness of these results, I evaluate the effect of divergent sentiment on two additional liquidity measures. Column 3 examines the impact of divergent sentiment on a firm's bid-ask spread, while column 4 evaluates the effect of divergent sentiment on share turnover.

The regression results in column 3 of Table 3 mirror the methodological approach in column 2, but with the bid-ask spread as the dependent variable. The findings are congruent with those in column 2, which show a persistent positive relationship between divergent sentiment and share liquidity. The t–3 lagged divergent sentiment measure is the lone exception, failing to demonstrate statistical significance at a .05 level or higher. In addition, the controlled variables yielded the expected results. Of note is the negative relationship of the Twitter>news sentiment dummy variables with share liquidity; however, none attained statistical significance at the .05 level or higher.

Similarly, column 4 of Table 3 delivers the regression results of the same method implemented in column 2, but with the logarithm of share turnover as the dependent variable. The findings align with those in column 2, indicating a continued positive relationship between divergent sentiment and share liquidity. The t–1 and t–3 lagged divergent sentiment measures are the lone exceptions to this trend, failing to reach statistical significance at the .01 level. Furthermore, the controlled variables yielded the expected results.

Intriguingly, the t–1 through t–4 Twitter>news sentiment dummy variables are positive and statistically significant at the .01 level, indicating that trading activity escalates when Twitter sentiment exceeds news sentiment. This observation corroborates the studies conducted by Dunham and Garcia (2020), who assert that the effect of Twitter sentiment on share liquidity surpasses that of conventional news media sentiment. This observation aligns with the proposition by Cookson et al. (2023) that investors' "echo chambers" on social networks can amplify bullish views more than bearish ones, potentially resulting in increased noise trading. Furthermore, consistent with earlier studies (e.g., Blankespoor et al., 2014), the findings demonstrate a positive relationship between the volume of tweets and news articles, and share turnover.

The robust relationship between divergent sentiment and enhanced liquidity using the alternative measures of bid-ask spread and turnover bolsters key theoretical models that delve into the effects of dispersion in investor opinions on financial markets. Models such as those proposed by Varian (1989) and Harris and Raviv (1993) formally demonstrate how investor belief differences spur speculative trading, which aligns with the consistent results across diverse empirical proxies for liquidity. The study further reaffirms this robust relationship by finding a consistent positive association between divergent sentiment and liquidity, regardless of the empirical measures used. Although this study focuses on divergent sentiment, unlike many models that directly scrutinize differences in investor opinions, the minor deviations from the observed theoretical benchmarks can be attributed to this distinction. Nonetheless, these findings fortify the fundamental theoretical foundations that connect disagreement with market activity.

Additionally, the positive correlation between divergent sentiment and liquidity affirms earlier empirical findings, such as those of Antweiler and Frank (2004) and Sprenger et al. (2014). These studies found a relationship between disagreement and extreme sentiment in online forums and increased trading activity. The robust results across liquidity proxies demonstrated in the present study further confirm the market impacts of divergent investor views documented in previous research.

In summary, the robustness of the results affirms the study's primary findings and consistency across all three share liquidity measures. In line with Hypothesis 1, the results consistently show that divergent sentiment is positively related to share liquidity.

B. Theoretical Mechanisms

The finding that a greater divergence between Twitter and news media sentiment predicts increased liquidity aligns with several theoretical mechanisms described in the literature. First, diverse interpretations of public signals and overconfidence in private information can give rise to heterogeneous valuations among investors (Hong and Stein, 2007; Odean, 1998). When sentiment diverges across information sources, it may indicate disagreement on fundamental value based on cognitive biases. Trading then occurs when investors act on discordant opinions and provide liquidity.

Second, selective attention and confirmation bias can lead investors to focus on sentiment signals from preferred sources, causing divergent interpretations (Peng and Xiong, 2006; Rabin and Schrag, 1999). Sentiment divergence, proxying for confirmation bias, can explain the relationship with liquidity. Third, Grossman and Stiglitz (1980) argue that gathering costly information incentivizes informed trading. If sentiment divergence captures informed trades based on Twitter or news signals, this could increase the volume and liquidity.

Overall, the association between divergent sentiment and liquidity aligns with multiple theoretical mechanisms related to differences in interpretation, cognitive bias, and information asymmetry. Disentangling the relative contributions of these drivers could deepen our understanding of the relationship between investor disagreement and market activity.

C. Pre- vs. Post-COVID Analysis

This section explores the differential impact of sentiment variations on share liquidity before and during the COVID-19 pandemic. A comprehensive analysis was performed to investigate the influence of sentiment divergence in the pre- and post-COVID periods, as shown in Table 4. This involved reevaluating the regression from Table 3, bifurcating the analysis into two distinct timeframes: (1) The period following the World Health Organization's formal declaration of COVID-19 as a pandemic on March 11, 2020, extending until April 30, 2021. (2) The interval from January 2015 to March 10, 2020, is considered the pre-COVID-19 pandemic era.

The results of the analysis are detailed in Table 4. Columns 1 and 2 display the results for the pandemic and pre-pandemic periods, respectively, using the Amihud measure as a proxy for share liquidity. Columns 3 and 4 use the bid-ask spread as a liquidity proxy, while columns 5 and 6 employ share turnover as a liquidity measure.

The findings in Table 4 reveal that sentiment divergence is positively related to liquidity during the pandemic period (Column 1). This corroborates prior findings in Table 3, which shows a positive relationship between lagged divergent sentiment measures and liquidity. However, it is noteworthy that the t–3 and t–5 lags and lagged dummy variables (signifying that Twitter sentiment exceeds news sentiment) were not statistically significant. Furthermore, the aggregate volume of news articles and tweets consistently enhances liquidity.

These findings are in agreement with Baig et al. (2021), who posit that the COVID-19 pandemic adversely impacted market liquidity, largely due to the surge in negative COVID-19 news that amplified investor anxiety. During the examined COVID-19 pandemic period, the median Amihud illiquidity measure increased by 92% relative to the pre-pandemic median.

In assessing the impact of a one standard deviation change in t–1 through t–5 divergent sentiment, the COVID-19 pandemic period recorded a 6.72% change in the median Amihud illiquidity measure. Conversely, a one standard deviation change in the pre-pandemic period results in a 12.30% change. Therefore, while sentiment divergence's overall impact was more substantial during the pandemic, the marginal effect normalized by the median Amihud value for each period revealed a reduced marginal effect.

The results in Table 4, column 3 (pandemic period), and column 4 (pre-pandemic period) demonstrate that divergent sentiment also significantly impacts liquidity when measured via bid-ask spreads, in line with the results from the Amihud measure. However, there were some notable differences.

Beginning with the post-pandemic period (column 3), the coefficient for divergent sentiment at t–2 is negative and statistically significant at the .05 level, while the t–1 and t–4 lagged divergent sentiment measures are also negative and statistically significant at the .10 level, suggesting that higher divergent sentiment reduces the bid-ask spread, indicating higher liquidity. However, the t–3 and t–5 coefficients were not statistically significant.

TABLE 3. Divergent Sentiment and Share Liquidity

	$\sqrt{\text{Amihud}}$	$\sqrt{\text{Amihud}}$	Bid-Ask Spread	Log (Turnover)
	(1)	(2)	(3)	(4)
Divergent Sentiment (t-1)		-0.0043***	-0.0078***	0.0045
Divergent Sentiment (t-2)		-0.0033***	-0.0034***	0.0208***
Divergent Sentiment (t-3)		-0.0020***	-0.0018	0.0255***
Divergent Sentiment (t-4)		-0.0026***	-0.0028**	0.0020
Divergent Sentiment (t-5)		-0.0024***	-0.0024**	0.0165***
Twitter >News Sent. Dummy (t-1)		-0.0004**	-0.0004	0.0094***
Twitter >News Sent. Dummy (t-2)		-0.0001	-0.0001	0.0082***
Twitter >News Sent. Dummy (t-3)		-0.0002	-0.0004	0.0086***
Twitter >News Sent. Dummy (t-4)		-0.0002	-0.0010*	0.0130***
Twitter >News Sent. Dummy (t-5)		0.0001	0.0000	0.0036
Log(Total News Stories Count+1)		0.0019***	0.0035***	0.0105***
Log(Total Tweets Count+1)		0.0023***	0.0069***	0.0535***
|Five-Day Average Return|	0.0035***	0.0028***	0.0058***	0.0854***
Log(Total Analysts+1)	-0.0098***	-0.0085***	-0.0426***	0.2809***
Log(Daily Share Price Volatility)	0.0106***	0.0086***	0.0290***	0.2514***
Beta	-0.0003	-0.0015	-0.0042*	0.2247***
Log (Market Cap.)	-0.0138***	-0.0175***	-0.0416***	-0.2411***
1/ Share Price	0.1410***	0.1331***	0.1764***	-0.7316***
Log (Share Turnover)	-0.0224***	-0.0246***	-0.0500***	n/a
VIX	0.0003***	0.0004***	0.0025***	0.0009**
Economic News Sentiment	0.0037*	0.0041*	0.0065	0.141***
Industry	Yes	Yes	Yes	Yes
Time (Year/Quarter)	Yes	Yes	Yes	Yes
Observations	174,232	174,232	174,232	174,232
Adjusted R^2	45.62%	46.78%	45.85%	49.35%
AIC	-612,130	-615,898	-295,679	278,690

(Continued)

TABLE 3. (Continued)

Note: Table 3 presents the pooled regression results relating divergent sentiment derived from Twitter and news media content to share liquidity. The dependent variable in columns 1–2 is the square root of the Amihud illiquidity measure for firm i, measured at time t. Column 3 uses the bid-ask spread taken as a percentage of the mid-price, column 4 utilizes the log of share turnover, and column 5 employs daily price volatility as the dependent variable, all at time t. All independent variables are lagged by one period unless otherwise noted. Appendix 1 provides a complete list and description of the variables used in this study. For brevity, the intercepts were suppressed. The coefficients were estimated using OLS, and the significance levels were based on robust standard error terms. Multicollinearity was assessed via variance inflation factors (VIFs), and all VIFs were found to be below 5, indicating that multicollinearity was not present. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Beginning in the post-pandemic period, an analysis of the coefficients provides key insights into divergent sentiment and its impact on liquidity. The coefficient for divergent sentiment at t–2 is negative and statistically significant at the 0.05 level, and those at t–1 and t–4 are also negative and significant at the .10 level. These findings imply that higher divergent sentiment narrows the bid-ask spread, indicating higher liquidity. However, the coefficients for t–3 and t–5 do not exhibit statistical significance, suggesting that the influence of divergent sentiment on liquidity via bid-ask spreads may manifest more immediately but wane more rapidly than the liquidity effect measured via the Amihud measure. This pattern is an intriguing departure from the results in column 1, where divergent sentiment at t–1 and t–2 was significant but the measures at t–3 and t–5 were not. Additionally, the coefficient for the lagged Twitter>News Sentiment Dummy variables is not statistically significant at the 0.05 level or better. Together, these findings illuminate a complex relationship between divergent sentiment and market liquidity and suggest that the temporal dynamics of these effects warrant further exploration.

Turning to the pre-pandemic period in column 4, the only statistically significant divergent sentiment measure is at t–1. This further supports the idea that the impact of divergent sentiment on liquidity is immediate, but also fades quickly. The Twitter>News Sentiment Dummy variable coefficients are not statistically significant in this period, suggesting that the relative sentiment between Twitter and news sources did not significantly impact liquidity via bid-ask spreads before the pandemic.

Columns 5 and 6 use the log of turnover as the liquidity measure. Turnover is a widely used measure of liquidity, with higher values corresponding to higher liquidity. Beginning with the post-pandemic period (column 5), all divergent sentiment measures from t–1 to t–3 are positive and statistically significant. This implies that elevated divergent sentiment boosts turnover and, consequently, liquidity for a duration of up to three days. This pattern is largely consistent with what was observed with the Amihud measure and the bid-ask spread.

Consistent with the earlier results, the Twitter>News Sentiment Dummy variables at t–1 and t–5 are not statistically significant during the pandemic, suggesting that the relative sentiment between Twitter and news sources does not significantly impact liquidity.

Looking at the pre-pandemic period (column 6), the divergent sentiment measures at t–3 and t–5 are positive and statistically significant at the .05 level, while the coefficients at t–1, t–2, and t–4 are not statistically significant. Furthermore, the Twitter>News Sentiment Dummy variables at t–1 and t–4 are statistically significant. This finding suggests that the relative sentiment between Twitter and news sources significantly impacts liquidity, as measured by turnover in the pre-pandemic period.

In summary, the absolute impact of divergent sentiment on share liquidity was more significant during the pandemic period. However, when normalized using the median Amihud value for each period, the marginal effect suggests diminished marginal influence. This trend was consistent even when the bid-ask spread was employed as an alternative liquidity proxy. Therefore, when considering the results in aggregate, the findings do not support H_2, leading to the conclusion that the effect of divergent sentiment on share liquidity was not more potent during the COVID-19 pandemic period.

Furthermore, when considering the influence of divergent sentiment on share liquidity, the findings align with prior research that reported increased trading activity during the COVID-19 pandemic, such as the work of Ortmann, Pelster and Wengerek (2020). Notably, the influence of divergent sentiment on share turnover was more potent and immediate during the pandemic era, indicating an upswing in noise trading, which subsequently enhanced share liquidity.

TABLE 4. Divergent Sentiment & Share Liquidity: Pre vs. Post COVID-19 Pandemic

	$\sqrt{\text{Amihud}}$	$\sqrt{\text{Amihud}}$	Bid-Ask Spread	Bid-Ask Spread	Log (Turnover)	Log (Turnover)
	3/11/20 *After (1)*	3/10/20 *Before (2)*	3/11/20 *After (3)*	3/10/20 *Before (4)*	3/11/20 *After (5)*	3/10/20 *Before (6)*
Divergent Sentiment (t–1)	-0.0050***	-0.0039***	-0.0055*	-0.0079***	0.0451***	-0.0017
Divergent Sentiment (t–2)	-0.0047***	-0.0029***	-0.0060**	-0.0023	0.0569***	0.0108*
Divergent Sentiment (t–3)	-0.0024*	-0.0022***	-0.0028	-0.0017	0.0508***	0.0182***
Divergent Sentiment (t–4)	-0.0027***	-0.0026***	-0.0045*	-0.0021	0.0179	-0.0013
Divergent Sentiment (t–5)	-0.0004	-0.0031***	-0.0021	-0.0021	0.0248*	0.0125**
Twitter>News Sent. Dummy (t–1)	0.0005	-0.0007***	-0.0006	-0.0001	-0.0009	0.0087**
Twitter>News Sent. Dummy (t–2)	0.0003	-0.0002	-0.0001	-0.0001	0.0050	0.0036
Twitter>News Sent. Dummy (t–3)	0.0011*	-0.0007***	0.0007	-0.0010	0.0012	0.0057*
Twitter>News Sent. Dummy (t–4)	-0.0005	-0.0001	-0.002*	-0.0006	-0.0067	0.0178***
Twitter>News Sent. Dummy (t–5)	0.0002	0.0000	-0.0008	0.0003	0.0022	0.0033
Log(Total News Stories Count+1)	0.0044***	0.0013***	0.0034***	0.0031***	0.0091**	0.0129***
Log(Total Tweets Count+1)	0.0016***	0.0023***	0.0029***	0.0078***	0.0758***	0.044***
$\lvert Five - DayAverageReturn \rvert$	0.0025***	0.0029***	0.0031***	0.0077***	0.0625***	0.095***
Log(Total Analysts+1)	-0.0076***	-0.0088***	-0.0427***	-0.0417***	0.1975***	0.3226***
Log(Daily Share Price Volatility)	0.0063***	0.0094***	0.0319***	0.0294***	0.3097***	0.2165***
Beta	0.008***	-0.0044***	-0.0051	-0.0018	0.0268	0.3261***
Log (Market Cap.)	-0.0203***	-0.0157***	-0.0380***	-0.0411***	-0.2457***	-0.2405***
1 / Share Price	0.1933***	0.1201***	0.3515***	0.1374***	-0.9948***	-0.6802***
Log (Share Turnover)	-0.0303***	-0.0216***	-0.0464***	-0.0506***	n/a	n/a
VIX	0.0002***	0.0002***	0.0019***	0.0009***	-0.0026***	0.0081***
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Time (Year/Quarter)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	44,213	130,019	44,213	130,019	44,213	130,019
Adjusted R^2	50.46%	45.36%	51.08%	41.51%	51.79%	48.56%

(Continued)

TABLE 4. (Continued)

Note: Table 4 reports pooled regression results relating divergent sentiment, derived from Twitter and news media content, to share liquidity. The dependent variable for columns 1 and 2 is the square root of the Amihud illiquidity measure firm i, measured at time t. The dependent variable for columns 3 and 4 is the daily bid-ask spread for firm i taken as a percentage of the mid-price, measured at time t, and the dependent variable for columns 5 and 6 is the log of share turnover. All independent variables are lagged one period unless otherwise noted. A complete list and description of the variables used in the study can be found in Appendix 1. Intercepts have been suppressed for brevity. The coefficients are estimated using OLS, and the significance levels are based on robust standard error terms. Multicollinearity is assessed via the variance inflation factors (VIFs), and all VIFs are found to be below 5, indicating multicollinearity is not present. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

D. Investor Attention and the Influence of Divergent Sentiment on Share Liquidity

The empirical results show that divergent sentiment is positively related to share liquidity. Previous research has found that investor attention is positively related to share liquidity (Ding and Hou, 2015; Fang and Peress, 2009; Fang et al., 2014). To delve deeper into the interplay between divergent sentiment and liquidity amidst varying degrees of investor attention, I present the effects of divergent sentiment on liquidity, operationalized through three daily investor attention proxies: news stories count, tweet volume, and the Bloomberg news heat index. Note that the Amihud illiquidity measure was used in these analyses, where higher values indicate lower liquidity.

Therefore, a positive relationship between divergent sentiment and the Amihud measure implies that greater divergent sentiment corresponds to lower illiquidity (i.e., greater liquidity).

Initially, I use the quantity of published news stories as a proxy for investor attention. I constructed a binary variable that takes the value of one if the company-specific news stories count for the preceding day exceeds the median value for all firms within the sample period. After incorporating the high-attention dummy variable and its interaction with lagged divergent sentiment into the primary model (Table 3, column 2), the results of this modified analysis are outlined in column 1 of Table 5.

These results echo the primary findings in column 2 of Table 3, reaffirming the prior conclusion about the positive effect of lagged divergent sentiment on share liquidity. Notably, there is a significant negative relationship (at a .05 level or better) between all lagged divergent sentiment measures (except for t–3) and share liquidity. Additionally, when investor attention at t-1 is categorized as high (marked by the high-attention dummy variable), a statistically significant decrease in share liquidity is observed, indicated by a negative coefficient. However, this effect reverses from t–2 to t-5, in which heightened investor attention correlates with decreased share liquidity, as evidenced by the positive and statistically significant coefficients.

The results further reveal a complex interaction between divergent sentiment and investor attention. When investor attention increases, the influence of divergent sentiment on share liquidity is amplified. Specifically, under high-attention conditions, the t–1 marginal effect of divergent sentiment exceeded its low-attention counterpart by approximately 18.6%. Nevertheless, from t–2 to t–5, the marginal effect of divergent sentiment under high investor attention diminishes, rendering it statistically insignificant. These findings underscore the critical role of divergent sentiment and investor attention in share liquidity fluctuations and highlight the importance of a temporal perspective in interpreting these relationships. Next, I substituted the high-attention binary variable used in Table 5, column 1, with a binary dummy variable indicating whether the previous day's tweet volume exceeded the median tweet volume for all firms during the sample period. The revised regression results are presented in Table 5 (column 2).

The outcomes of column 2 align closely with those of column 1, indicating that t–1 through t–5 divergent sentiment measures maintain a positive relationship with share liquidity, reaching statistical significance at a .05 level or higher. Similarly, the t–1 dummy variable indicating high investor attention is statistically significant at the .01 level, indicating an increase in liquidity with elevated investor attention. Nevertheless, as in column 1, this effect reverses during the t–2 through t–5 periods.

Further, I use the Bloomberg News Heat Index as an investor attention measure. Bloomberg tracks the number of news publications for most firms and reports the unexpected publication activity over the prior 24-hour period compared to the last 45 days. Bloomberg assigns a daily score of 1, 2, 3, or 4 if the daily number of news publications is between 80% and 90%, between 90% and 96%, between 96% and 98%, or greater than 98% of the previous 45 days' count, respectively. I create a high-attention dummy variable using the Bloomberg News Heat Index score to examine the relationship between investor attention and share liquidity. This dummy variable was set to 1 if the news heat index was in the top 80th percentile . I then run the primary regression from Table 3, column 2, including the high-attention dummy variable and the interaction between the lagged divergent sentiment measures and the high-attention dummy variable. The results of this analysis are presented in Table 5, column 3.

These findings are consistent with those from columns 1 and 2, indicating a positive relationship between t–1 through t–5 divergent sentiment measures and share liquidity, which is statistically significant at the .01 level. However, only the t–2 dummy variable for high investor attention is statistically significant, suggesting a positive correlation between investor attention and share liquidity.

Moreover, both t–1 and t–2 divergent sentiment marginal effects are statistically significant when investor attention is high. However, the t–1 marginal effect under high attention was less potent than that under low attention. In contrast, the t–2 divergent sentiment's marginal effect under high investor attention exceeds that of its low-attention counterpart. Therefore, these results do not definitively confirm that greater investor attention amplifies the impact of divergent sentiment on share liquidity.

In conclusion, the results in Table 5 offer partial support for the conjecture that the positive impact of divergent sentiment on share liquidity is amplified under conditions of heightened investor attention.

E. Robustness Check

To further validate the robustness of the primary findings linking divergent sentiment to share liquidity, I conduct additional tests using an alternative divergent sentiment metric, as shown in Table 6. This alternative measure was calculated to confirm that the results were not sensitive to the specific construction of the divergent sentiment variable. In this context, the divergent sentiment ratio (DSR) was introduced as an alternative measure to gauge the divergence between daily Twitter content and news sentiment. The DSR process involves four stages: (1) normalization, shifting the original sentiment values (-1 to +1) upward by 1.0001, resulting in a range from 0.0001 to 2.0001; (2) ratio computation, dividing the revised Twitter sentiment by the news sentiment, establishing a foundational comparison; (3) extreme outliers in the ratio are winsorized at the 99.5% level; and (4) divergence is measured as the absolute value of 1 (parity) minus the computed ratio. The DSR provides an intuitive way to quantify divergence, with higher values indicating greater divergence. Formally, the DSR is defined as:

TABLE 5. Investor Attention and the Influence of Divergent Sentiment on Share Liquidity

	$\sqrt{\text{Amihud}}$		
	News Stories Count	Tweets Count	Bloomberg News Heat
	(1)	(2)	(3)
Divergent Sentiment (t–1)	-0.0043***	-0.0040***	-0.0042***
Divergent Sentiment (t–2)	-0.0029***	-0.0021***	-0.0034***
Divergent Sentiment (t–3)	-0.0008	-0.0014**	-0.0018***
Divergent Sentiment (t–4)	-0.0019***	-0.0015**	-0.0022***
Divergent Sentiment (t–5)	-0.0017**	-0.0018***	-0.0022***
High Attention Dummy (t–1)	-0.0028***	-0.0030***	-0.0004
High Attention Dummy (t–2)	0.0020***	0.0025***	-0.0018***
High Attention Dummy (t–3)	0.0032***	0.0030***	-0.0002
High Attention Dummy (t–4)	0.0036***	0.0042***	0.0003
High Attention Dummy (t–5)	0.0015***	0.0018***	0.0003
Div. Sent. (t–1) x High Att. Dummy	0.0019**	0.0014	0.0009
Div. Sent. (t–2) x High Att. Dummy	-0.0011	-0.0026***	0.0006
Div. Sent. (t–3) x High Att. Dummy	-0.0040***	-0.0023***	-0.0002
Div. Sent. (t–4) x High Att. Dummy	-0.0028***	-0.0034***	-0.0009
Div. Sent. (t–5) x High Att. Dummy	-0.0015*	-0.0015*	0.0002
News & Tweet Total Counts	Yes	Yes	Yes
Firm & Market Sent. Controls	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Time (Year/Quarter)	Yes	Yes	Yes
Observations	174,232	174,232	168,681
Adjusted R^2	46.95%	46.96%	47.23%
AIC	-616,424	-616,480	-614,067
Marginal Effects			
High Attention (t–1)	-0.0051***	-0.0056***	-0.0036**
Low Attention (t–1)	-0.0043***	-0.0040***	-0.0042***
High Attention (t–2)	-0.0019	-0.0022	-0.0047***
Low Attention (t–2)	-0.0029***	-0.0021***	-0.0034***
High Attention (t–3)	-0.0015	-0.0007	-0.0022
Low Attention (t–3)	-0.0008	-0.0014**	-0.0018***
High Attention (t–4)	-0.0011	-0.0007	-0.0027
Low Attention (t–4)	-0.0019***	-0.0015**	-0.0022***
High Attention (t–5)	-0.0017	-0.0015	-0.0017
Low Attention (t–5)	-0.0017**	-0.0018***	-0.0022***

Note: Table 5 reports pooled regression results relating divergent sentiment, derived from Twitter and news media content, to share liquidity. The dependent variable is the square root of the Amihud illiquidity measure firm i, measured at time t. All independent variables are lagged one period unless otherwise noted. The high attention dummy variable for columns 1 and 2 is set to 1 when news stories and tweet counts are greater than the sample median.The coefficients are estimated using OLS, and the significance levels are based on robust standard error terms. Multicollinearity is assessed via the variance inflation factors (VIFs), and all VIFs are found to be below 5, indicating multicollinearity is not present. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

$$\text{DivergentSentimentRatio}_{i,t} = \left|1 - \frac{\text{TwitterSentiment}_{i,t} + 1.0001}{\text{NewsSentiment}_{i,t} + 1.0001}\right| \tag{3}$$

Re-estimating the main regression models using this alternative divergence metric generated consistent results, as shown in Table 6. The DSR retains a statistically significant positive relationship with liquidity across all specifications. For the Amihud measure (column 1), bid-ask spread (column 2), and share turnover (column 3), the lagged DSR coefficients have the expected signs and almost uniformly achieve significance at the .05 level or higher, except for the DSR t–4 lag for turnover, which is significant at the .10 level.

These robustness tests affirmed the validity of the original findings by corroborating them using a different construction of divergent sentiment. Regardless of the divergence metric employed, a consistent positive association between divergent sentiment and liquidity holds. This greatly strengthens the conclusions of this study by demonstrating its invariance in the operationalization of divergent sentiment.

In summary, the additional analysis with an alternative divergence measure provides strong confirming evidence that substantiates the reliability of the paper's main results. The relationship between divergent sentiment and liquidity appears robust across multiple divergence proxies, lending greater credibility to the findings.

V. Conclusion

The existing research acknowledges the substantial impact of divergent investor opinions on share liquidity. However, the impact of sentiment divergence originating from different media platforms, including Twitter and traditional news articles, on share liquidity has not been investigated thoroughly. This study fills this gap by examining the impact of divergent sentiment stemming from Twitter and news media content on share liquidity from January 2015 to April 2021. Utilizing daily measurements of Amihud illiquidity, bid-ask spread, and share turnover as liquidity proxies, along with divergent sentiment data (tweet sentiment minus news sentiment), this study finds that divergent sentiment is positively related to share liquidity. This finding aligns with the theoretical prediction that investor opinion divergence increases trading activity and liquidity.

TABLE 6. Robustness Regressions

	$\sqrt{\text{Amihud}}$	Bid-Ask Spread	Log(Turnover)
	(1)	(2)	(3)
Divergent Sentiment Ratio (t–1)	-0.0013***	-0.0026***	0.0067***
Divergent Sentiment Ratio (t–2)	-0.0009***	-0.0021***	0.0088***
Divergent Sentiment Ratio (t–3)	-0.0004**	-0.0012**	0.0110***
Divergent Sentiment Ratio (t–4)	-0.0006***	-0.0013***	0.0035*
Divergent Sentiment Ratio (t–5)	-0.0004***	-0.0013**	0.0108***
Twitter >News Sentiment Dummy (t–1)	0.0001	0.0006	0.0070**
Twitter >News Sentiment Dummy (t–2)	0.0004	0.0008	0.0041
Twitter >News Sentiment Dummy (t–3)	0.0002	0.0003	0.0038
Twitter >News Sentiment Dummy (t–4)	0.0001	-0.0005	0.0113***
Twitter >News Sentiment Dummy (t–5)	0.0003	0.0003	0.0005
Log(Total News Stories Count + 1)	0.0019***	0.0035***	0.0102***
Log(Total Tweets Count + 1)	0.0023***	0.0069***	0.0534***
$\lvert Five - DayAverageReturn \rvert$	0.0026***	0.0057***	0.0857***
Log(Total Analysts + 1)	-0.0088***	-0.0428***	0.2813***
Log(Daily Share Price Volatility)	0.0085***	0.0288***	0.2516***
Beta	-0.0012	-0.0040	0.2245***
Log(Market Cap.)	-0.0174***	-0.0417***	-0.2404***
1 / Share Price	0.1337***	0.1769***	-0.7323***
Log(Share Turnover)	-0.0247***	-0.0499***	n/a
VIX	0.0004***	0.0025***	0.0009**
Economic News Sentiment	0.0043**	0.0067	0.1408***
Industry	Yes	Yes	Yes
Time (Year/Quarter)	Yes	Yes	Yes
Observations	174,232	174,232	174,232
Adjusted R^2	46.71%	45.86%	49.46%
AIC	-615,648	-295,717	278,619

Note: Table 6 presents pooled regression results relating the divergent sentiment ratio derived from Twitter and news media content to share liquidity. The dependent variable in column 1 is the square root of the Amihud illiquidity measure for firm i, measured at time t. Column 2 uses the bid-ask spread taken as a percentage of the mid-price, column 3 utilizes the log of share turnover, and column 5 employs daily price volatility as dependent variables, all at time t. All independent variables are lagged one period unless otherwise noted. A complete list and description of the variables used in the study can be found in Appendix 1. Intercepts have been suppressed for brevity. The coefficients are estimated using OLS, and the significance levels are based on robust standard error terms. Multicollinearity is assessed via the variance inflation factors (VIFs), and all VIFs are found to be below 5, indicating multicollinearity is not present. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

This study provides new empirical insights into the interplay between share liquidity and divergent investor sentiment. This study contributes significantly to the literature on liquidity and investor behavior by evaluating the impact of divergent sentiment extracted from tweets and news media content on share liquidity. Specifically, the findings affirm Grossman and Stiglitz's (1980) and Hellwig's (1980) models, suggesting that heterogeneous information is incorporated into prices through trading. The results also provide credence to Harris and Raviv 's (1993) and Varian's (1989) frameworks, which posit that diverse investor opinions incentivize speculative trading and improve liquidity. However, the identified systematic predictive relationship poses a potential challenge to the strong-form Efficient Market Hypothesis, pointing to inefficiencies.

The results also connect to the theoretical models of liquidity determination and the origins of trading activity. However, this relationship conflicts with models hypothesizing that disagreement can reduce liquidity under certain conditions (Holden and Subrahmanyam, 1992). Moreover, the results lend credibility to behavioral finance theories that link cognitive biases to disagreement and increased market activity (Odean, 1998; Rabin and Schrag, 1999). However, the consistent predictive ability of sentiment divergence suggests a significant behavioral influence on liquidity.

This study reveals divergent sentiment as an important driver of liquidity while surfacing areas for theoretical refinement. Specifically, future studies should explore the conditions under which heterogeneous beliefs enhance or diminish liquidity. Scholars should also examine the practical implications of these findings, such as how firms can monitor divergent sentiment to forecast liquidity changes.

In summary, by establishing a relationship between share liquidity and divergent investor sentiment, this study makes important strides by connecting these two domains. The conclusions provide fruitful directions for researchers and practitioners seeking to further unravel the complex dynamics between investor disagreement and share liquidity.

References

Amihud, Y. 2002. Cross-section and time-series effects: cross-section and time-series effects. *Journal of Financial Markets* 5: 31-56.

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

Baig, A. S.; Butt, H. A.; Haroon, O.; and Rizvi, S. A. R. 2021. Deaths, panic, lockdowns and U.S. equity markets: The case of COVID-19 pandemic. *Finance Research Letters* 38: 101701

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

Bali, T. G.; Hirshleifer, D. A.; Peng, L.; and Tang, Y. 2021. Attention, Social Interaction, and Investor Attraction to Lottery Stocks (No. w29543). *National Bureau of Economic Research.*

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

Barber, B. M., and Odean, T. 2001. Boys will be boys: Gender, overconfidence, and common stock investment. *The Quarterly Journal of Economics* 116(1): 261-292.

Barberis, N.; Shleifer, A.; and Vishny, R. 1998. A model of investor sentiment. *Journal of Financial Economics* 49(3): 307-343.

Bartov, E.; Faurel, L.; and Mohanram, P. 2018. Can Twitter Help Predict Firm-Level Earnings and Stock. *The Accounting Review* 93(3): 25–57.

Behrendt, S., and Schmidt, A. 2018. The Twitter myth revisited: Intraday investor sentiment, Twitter activity and individual-level stock return volatility. *Journal of Banking and Finance* 96: 355–367.

Blankespoor, E.; Miller, G. S.; and White, H. D. 2014. The Role of Dissemination in Market Liquidity: Evidence From Firms' Use of Twitter. *The Accounting Review* 89(1): 79–112.

Bollen, N.; Smith, T.; and Whaley, R. 2004. Modeling the Bid/Ask Spread: Measuring the Inventory Holding Period. *Journal of Financial Economics* 72(1): 97–141.

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

Boudoukh, J.; Feldman, R.; Kogan, S.; and Richardson, M. 2018. Information, trading, and volatility: Evidence from 2emfirm-specific news. *The Review of Financial Studies* 32(3): 992–1033.

Bowen, R. M.; Chen, X.; and Cheng, Q. 2008. Analyst coverage and the cost of raising equity capital: Evidence from 2emunderpricing of seasoned equity offerings. *Contemporary Accounting Research* 25(3): 657–700.

Brennan, M. J.; Chordia, T.; and Subrahmanyam, A. 1998. Alternative factor specifications, security characteristics, and the 2em cross-section of expected stock returns. *Journal of Financial Economics* 49(3): 345-373.

Brennan, M.; Huh, S. W.; and Subrahmanyam, A. 2013. An analysis of the Amihud illiquidity premium. *The Review of Asset Pricing Studies* 3(1): 133-176.

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

Chang, Y.-C.; Hong, H. G.; Tiedens, L.; and Zhao, B. 2015. Does diversity lead to diverse opinions? Evidence from languages and stock markets. *SSRN Electronic Journal*.

Chen, H.; De, P.; Hu, Y.; and Hwang, B. H. 2014. Wisdom of crowds: The value of stock opinions transmitted through social media. *Review of Financial Studies* 27(5): 1367–1403.

Chordia, T.; Huh, S. W.; and Subrahmanyam, A. 2009. Theory-based illiquidity and asset pricing. *Review of Financial Studies* 22(9): 3629–3668.

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

Chordia, T.; Subrahmanyam, A.; and Roll, R. 2000. Commonality in liquidity. *Journal of Financial Economics* 56: 3–28.

Chung, K. H.; Elder, J.; and Kim, J. C. 2010. Corporate governance and liquidity. *Journal of Financial and Quantitative sAnalysis* 45(2): 265–291.

Chung, K. H., and Zhang, H. 2014. A simple approximation of intraday spreads using daily data. *Journal of Financial Markets* 17: 94–120.

Cookson, J. A.; Engelberg, J. E.; and Mullins, W. 2023. Echo chambers. *Review of Financial Studies* 36(2): 450–500.

Cookson, J. A., and Niessner, M. 2020. Why don't we agree? Evidence from a social network of investors. *Journal of Finance* 75(1): 173–228.

Datar, V. T.; Naik, N. Y.; and Radcliffe, R. 1998. Liquidity and stock returns: An alternative test. *Journal of Financial Markets* 1(2): 203–219.

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

Demsetz, H. 1968. The cost of transacting. *Quarterly Journal of Economics* 82(1): 33–53.

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

Ding, R., and Hou, W. 2015. Retail investor attention and stock liquidity. *Journal of International Financial Markets, Institutions and Money* 37: 12–26.

Dunham, L. M., and Garcia, J. 2020. Measuring the effect of investor sentiment on liquidity. *Managerial Finance* 47(1): 59–85.

Dunham, L. M., and Garcia, J. 2021. Measuring the effect of investor sentiment on financial distress. *Managerial Finance* 47(12): 1834–1852.

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

Fang, L. H.; Peress, J.; and Zheng, L. 2014. Does media coverage of stocks affect mutual funds' trading and performance? *Review of Financial Studies* 27(12): 3441–3466.

Ferguson, N. J.; Philip, D.; Lam, H.; and Guo, J. M. 2015. Media content and stock returns: The predictive power of press. *Multinational Finance Journal* 19(1): 1–31.

Fong, K. Y.; Holden, C. W.; and Trzcinka, C. A. 2017. What are the best liquidity proxies for global research? *Review of Finance* 21(4): 1355–1401.

Garcia, D. 2013. Sentiment during recessions. *The Journal of Finance* 68(3): 1267–1300.

Garcia, J. 2021. Analyst herding and firm-level investor sentiment. *Financial Markets and Portfolio Management* 35: 461–494.

Garcia, J. 2022. Analysts' stock ratings and the predictive value of news and Twitter sentiment. *Investment Analysts Journal* 51(4): 236–252.

Giannini, R.; Irvine, P.; and Shu, T. 2019. The convergence and divergence of investors' opinions around earnings news: Evidence from a social network. *Journal of Financial Markets* 42: 94–120.

Goldstein, I., and Yang, L. 2015. Information diversity and complementarities in trading and information acquisition. *Journal of Finance* 70(4): 1723–1765.

Glosten, L. R., and Milgrom, P. R. 1985. Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics* 14(1): 71–100.

Grossman, S. J., and Stiglitz, J. E. 1980. On the impossibility of informationally efficient markets. *The American Economic Review* 70(3): 393–408.

Gu, C., and Kurov, A. 2020. Informational role of social media: Evidence from Twitter sentiment. *Journal of Banking and Finance* 121(105969).

Halim, E.; Riyanto, Y. E.; and Roy, N. 2019. Costly information acquisition, social networks, and asset prices: Experimental evidence. *Journal of Finance* LXXIV(4): 1975–2010.

Han, B., and Yang, L. 2013. Social networks, information acquisition, and asset prices. *Management Science* 59(6): 1444–1457.

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

Hasbrouck, J., and Seppi, D. 2001. Common factors in prices, order flows, and liquidity. *Journal of Financial Economics* 59: 383–411.

Hellwig, M. F. 1980. On the aggregation of information in competitive markets. *Journal of Economic Theory* 22(3): 477–498.

Holden, C. W., and Subrahmanyam, A. 1992. Long-lived private information and imperfect competition. *The Journal of Finance* 47(1): 247–270.

Hong, L., and Page, S. E. 2004. Groups of diverse problem solvers can outperform groups of high-ability problem solvers. *Proceedings of the National Academy of Sciences of the United States of America* 101(46): 16385–16389.

Hong, H., and Stein, J. C. 2007. Disagreement and the stock market: Theory and empirical evidence. *Journal of Economic Perspectives* 21(2): 109–128.

Jegadeesh, N., and Wu, D. 2013. Word power: A new approach for content analysis. *Journal of Financial Economics* 110.

Kelley, E. K., and Tetlock, P. C. 2013. Why do investors trade? *SSRN*.

Kruger, S. 2020. Disagreement and liquidity. *SSRN Electronic Journal*.

Kyle, A. S. 1985. Continuous Auctions and Insider Trading. *Econometrica* 53(6): 1315–1335.

Kyle, A. S.; Obizhaeva, A. A.; and Wang, Y. 2018. Smooth trading with overconfidence and market power. *Review of Economic Studies* 85(1): 611-662.

Lee, J., and Chung, K. H. 2018. Foreign Ownership and Stock Market Liquidity. *International Review of Economics and Finance* 54: 311–325.

Liu, S. 2015. Investor Sentiment and Stock Market Liquidity. *Journal of Behavioral Finance* 16(1): 51–67.

Llorente, G.; Michaely, R.; Saar, G.; and Wang, J. 2002. Dynamic volume-return relation of individual stocks. *The Review of Financial Studies* 15(4): 1005–1047.

Loughran, T., and Mcdonald, B. 2016. Textual Analysis in Accounting and Finance: A Survey. *Journal of Accounting Research* 54(4): 1187–1230.

Loewenstein, G. F.; Hsee, C. K.; Weber, E. U.; and Welch, N. 2001. Risk as Feelings. *Psychological Bulletin* 127(2): 267–286.

Newey, W. K., and West, K. D. 1987. A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica* 55(3): 703–708.

Newey, W. K., and West, K. D. 1994. Automatic lag selection in covariance matrix estimation. *The Review of Economic Studies* 61(4): 631–653.

Odean, T. 1998. Volume, Volatility, Price, and Profit When All Traders Are Above Average. *The Journal of Finance* 53(6): 1887–1934.

Ortmann, R.; Pelster, M.; and Wengerek, S. T. 2020. COVID-19 and investor behavior. *Finance Research Letters* 37: 101717.

Pedersen, L. H. 2022. Game on: Social networks and markets. *Journal of Financial Economics* 146(3): 1097–1119.

Peng, L.; and Xiong, W. 2006. Investor attention, overconfidence and category learning. *Journal of Financial Economics* 80(3): 563–602.

Rabin, M., and Schrag, J. L. 1999. First impressions matter: A model of confirmatory bias. *The Quarterly Journal of Economics* 114(1): 37–82.

Scheinkman, J. A., and Xiong, W. 2003. Overconfidence and speculative bubbles. *Journal of Political Economy* 111(6): 1183–1219.

Shapiro, A. H.; Sudhof, M.; Wilson, D.; and Shapiro, A. H. 2020. Measuring News Sentiment. *Journal of Econometrics* 228(2): 221-243.

Sprenger, T. O.; Tumasjan, A.; Sandner, P. G.; and Welpe, I. M. 2014. Tweets and trades: The information content of stock microblogs. *European Financial Management* 20(5): 926–957.

Statman, M.; Thorley, S.; and Vorkink, K. 2006. Investor overconfidence and trading volume. *The Review of Financial Studies* 19(4): 1531–1565.

Tetlock, P. C. 2007. Giving Content to Investor Sentiment: The Role of Media in the Stock Market. *Journal of Finance* 62(3): 1139–1168.

Tetlock, P. C.; Saar-Tsechansky, M.; and Macskassy, S. 2008. More than Words: Quantifying Language to Measure Firms' Fundamentals. *The Journal of Finance* 63(3): 1437–1467.

Varian, H. R. 1989. Differences of opinion in financial markets. Chapter 3. In C. Stone (Ed.), *Financial risk: Theory, evidence and implications*. Springer: 3–37.

Whaley, R. E. 2000. The Investor Fear Gauge. *The Journal of Portfolio Management* 26(3): 12–17.

Wooldridge, J. M. 2010. *Econometric Analysis of Cross Section and Panel Data*. Cambridge, England: MIT Press.

Appendix 1: Variable Definitions

Variable	Definition
Bid-Ask Spread	The daily average of all bid-ask spreads is taken as a percentage of the mid-price.
Amihud Illiquidity	Amihud's (2002) illiquidity measure calculated as follows:
Daily Share Turnover	Total number of shares traded on a firm on the current day divided by the total current number of shares outstanding.
DivergentSentiment ($\lvert Twitter–NewsSent.\rvert$)	The absolute value of the Twitter media daily sentiment average less the news media daily sentiment average. Both sentiment measures range from -1 (most negative) to 1 (most positive), with 0 indicating neutral sentiment.
Divergent Sentiment Ratio	The divergent sentiment ratio is used as a robustness measure to the primary divergent sentiment measure. It is computed as follows:
Twitter $>$ News Sent. Dummy	A dummy variable indicating when the daily Twitter media sentiment is greater than the daily news media sentiment.
Total News Stories Count	The total number of news stories published in each trading day.
Total Tweets Count	The total number of tweets published in each trading day.
$\lvert Five - DayAverageShareReturn\rvert$	The absolute value of the rolling five-day average of the day-to-day total share return values.
Total Analysts	The total number of analysts rating the company at the close of each trading day.
Daily Share Price Volatility	The daily share price volatility measured as the intraday trading range (high price minus low price) divided by the previous day closing share price.
Beta	It measures the volatility of the stock price relative to the volatility in the market index. Beta is the percent change in the price of the stock given a 1% change in the market index. It is computed via a regression of the historical trading prices of the stock against the S&P 500 using weekly data over a two-year period.
Market Capitalization	The total current market value of all of the company's outstanding shares, calculated at the close of each trading day.
1/ Share Price	The inverse of the daily closing share price.
VIX	The Chicago Board Options Exchange Market Volatility Index.
Economic News Sentiment	The sentiment scores for economics-related news articles using a lexical approach compiled using a historical archive of news articles from 16 major U.S. newspapers (Shapiro et al., 2020).
Bloomberg News Heat	A high-attention dummy variable is created based on the Bloomberg news heat index score. If the news heat index is in the top 80th percentile, the dummy variable is set to 1. Bloomberg monitors news publication counts for companies and compares the unexpected activity in the past 24 hours to the previous 45 days.
Industry	The Global Industry Classification Standard (GICS) is used to classify each firm into one of the 11 sectors in the GICS.