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RESEARCH ARTICLE

The Impact of Retail Investors' Attention on Stock Liquidity over Different Time Horizons

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ABSTRACT

Retail investors in emerging markets often lack the support afforded to their counterparts in developed markets. Excessive focus on the influence of institutional investors can lead to the underestimation of retail investors' roles and their potential impact on capital market efficiency. This study aims to examine the importance of retail investors' contributions to stock liquidity in the Iranian capital market, an emerging market. A sample of 111 companies listed on the Tehran Stock Exchange was selected, and the impact of retail investor attention on stock liquidity was tested over short-term, medium-term, and long-term horizons using ordinary least squares regression and trend analysis. The analysis reveals that retail investor attention significantly positively affects future stock liquidity in the short term. However, as the time horizon extends, this effect diminishes and reverses in the long term. These findings remained robust when the proxy for retail investor attention was modified. This research highlights the substantial influence of retail investors in emerging markets and their potential to improve market efficiency. The results offer valuable insights for policymakers, regulators, and corporate managers in similar emerging markets, emphasizing the critical role that retail investors play.

Introduction

Investment risk is influenced by various factors, including the liquidity of securities. One of the primary functions of the capital market is to enhance the liquidity of securities. Consequently, when assessing stock market development, liquidity is a key indicator (Kouki & Guizani, 2009). Given its importance, many researchers have examined the impact of various factors on stock liquidity over time. This paper aims to explore the dynamic relationship between retail investor attention and stock liquidity across short-term, medium-term, and long-term horizons.

Stock liquidity refers to the speed and ease with which investors can buy or sell stocks without causing significant price changes. In other words, liquidity is the capacity to quickly convert an asset into cash without substantial value loss (Huberman & Halka, 2001; Miralles-Quirós et al., 2017; Tripathi & Dixit, 2020). Additionally, as a factor of market efficiency, liquidity significantly influences transaction costs, expected returns, and financial market stability (Chordia et al., 2008; Pástor & Stambaugh, 2003). This study examines stock liquidity from the perspective of the limited attention theory (Kahneman, 1973; Pashler et al., 2001). According to this theory, "attention" requires cognitive effort and uses limited mental resources. Because of the limited availability of these resources and the vast information available, individuals encounter a psychological constraint known as "limited attention." Thus, people cannot process all available information simultaneously and tend to focus on topics that are more appealing to them.

Evidence suggests that increased retail investor attention correlates with higher net retail purchases (Cheng et al., 2021), which could also influence stock liquidity. Barber and Odean (2008) support this idea, noting that retail investors often buy stocks that capture their attention due to the abundance of choices and constraints of time and attention. This behavior may lead to increased net buying and rapid changes in stock prices and trading volumes in the short term (Adachi et al., 2017). Accordingly, this study investigates the effect of retail investor attention on stock liquidity across various time horizons in the Iranian stock market which is an emerging market.

Examining retail investors' attention in an emerging market context offers multiple contributions to the financial literature. First, given the constraints—such as sanctions and political-economic changes—that have influenced the development of Iran's capital market in recent years, examining factors like retail investor attention can provide valuable insights into the limitations and characteristics of emerging markets. This, in turn, can inform strategies for improving market efficiency and fostering growth. Second, retail investors represent a crucial and influential investor group in the Iranian stock market. With the depreciation of the national currency and inflationary pressures, their engagement in the

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market has increased significantly in recent years. As a result, heightened attention to a stock by retail investors can directly affect its trading volume and market value. Understanding the impact of retail investor attention on stock liquidity, therefore, has the potential to increase transparency and efficiency in capital markets across other emerging economies with similar characteristics. Third, in emerging markets, information and support for retail investors are typically less available than in developed markets. Various factors, including political-economic shifts and low transparency in corporate performance, can inadvertently impact trading volumes and stock liquidity. Examining retail investor attention—a factor sensitive to such influences—can provide insights into the efficiency of the capital market. As such, this research is valuable for investors and analysts, as well as policymakers and regulatory authorities overseeing emerging capital markets.

The remainder of the paper is structured as follows. Section 2 provides a literature review and presents the research hypotheses. Sections 3 and 4 describe the sample characteristics, research data, and the methods used to calculate research variables. Section 5 outlines the hypothesis testing methods, while Section 6 presents the hypothesis testing results. Section 7 focuses on sensitivity analysis, and Section 8 concludes with implications for research and practice.

Literature Review and Research Hypotheses

Stock Liquidity and Its Concepts

Financial decisions are based on a balance between risk and return. To achieve a specific return, it is important to consider a certain level of risk. One of the most significant factors that explains the risk of stocks is stock liquidity, as it impacts investment decisions when forming a portfolio (Ma et al., 2021). Liquidity refers to the ability to trade a large volume of securities quickly and at a low cost, without significantly affecting the price between the time of the order and purchase (Alizadeh et al., 2021; Liu, 2006). While liquidity is not directly observable, two quantities that are related to it are spread and depth. Spread refers to the difference between the bid and ask prices, while depth is the combined number of stocks bid at the bid price and offered at the asking price (Carlston, 2018; Huberman & Halka, 2001). These measures indicate the speed and ease of trading.

The financial literature shows that there are various methods for measuring stock liquidity depending on its nature. In several studies, including Stoll (1978), Morse and Ushman (1983), Ryan (1996), and Boone (1998), the bid-ask spread has been used as a measure of liquidity. The results of these studies indicate that wider bid-ask spreads reduce liquidity. The Amihud illiquidity measure, which measures the stock market price responsiveness to order flows, is another measure of stock liquidity (Amihud, 2002). The logic behind this measure is that if a stock price changes significantly in response to a small volume of trades, the stock is less liquid (i.e., the Amihud illiquidity measure is high for that stock). The turnover ratio, a measure of liquidity that indicates the frequency or number of times an asset is traded, has a positive relationship with market liquidity (Chan et al., 2008). The higher the turnover ratio (i.e., the number of shares traded relative to the total shares outstanding and sold), the higher the market liquidity.

Illiquidity is primarily caused by information asymmetry, a condition in which one party in a relationship has better or more information than the other (Bergh et al., 2019; Chen & McMillan, 2020). Investors naturally demand more information to reduce the costs associated with information asymmetry before making financial decisions (Drake et al., 2012; Peng & Xiong, 2006; Vlastakis & Markellos, 2012). As a result, investor rationality suggests that information demand increases with information asymmetry (Aouadi et al., 2018). Previous models (e.g., Glosten & Milgrom, 1985; Kyle, 1985) were primarily based on the assumption that investors have infinite information processing abilities and that all relevant information available is instantaneously processed and incorporated into stock prices (Fama, 1970). However, this assumption is not necessarily true, and investors have limited cognitive resources. As a result, the costs of acquiring information, such as tracking, collecting, and processing firm news, limit the set of information that investors can analyze (Barber & Odean, 2008; Merton, 1987). Given these limitations, many investors consider purchasing only stocks that have first caught their attention (Barber & Odean, 2008). Consequently, new information cannot be automatically incorporated into stock prices until it attracts investors' attention and affects stock liquidity (Aouadi et al., 2018). This issue is further explained in the following sections.

Investor Attention and Its Limitations

Standard asset pricing models are built on the assumption that markets quickly and accurately process new information to determine asset values. However, recent research suggests that important news or information may not be reflected in prices until investors begin to pay attention to them (Ballinari et al., 2022; Frydman & Wang, 2020; Hirshleifer et al., 2009; Huberman & Regev, 2001; Jiang et al., 2016; Peng & Xiong, 2006; Rasool & Ullah, 2020; Soltani et al., 2023). The "limited attention theory", proposed by Kahneman (1973), argues that attention is a scarce cognitive resource for humans. This means that when investors make decisions, they must selectively process information because there is a vast amount of available information and limited attention to process it all. As a result, investors are inevitably constrained in their ability to process information, which can impact their investment decisions.

There are many direct and indirect proxies used to measure the level of investor attention given to a particular stock. Indirect proxies include a company's size, age, securities listing period (Barry & Brown, 1984, 1986), level of analyst coverage (Arbel & Strebel, 1983), financial institution holdings (Arbel et al., 1983), diversity of analyst opinion (Barry & Jennings, 1992), advertising intensity (Grullon et al., 2004), presentations to analysts (Francis et al., 1997), media coverage (Fang & Peress, 2009), news and headlines (Barber & Odean, 2008; Yuan, 2008), trading volume (Barber & Odean, 2008; Gervais et al., 2001), and net-buying (Cheng et al., 2021). However, these indirect criteria do not guarantee that investors will pay attention to them (Adachi et al., 2017). For instance, advertising intensity, news, and media coverage may not be widely known among investors. In addition, increases in trading volumes and net-buying could result from market manipulation by a small or specific group of investors, making it a poor indicator of market-wide investor attention (Tantaopas et al., 2016). On the other hand, some metrics directly measure investors' attention to a particular stock by relying on their search activity. An investor who pays attention to a specific stock searches for new information about it. In recent decades, thanks mostly to the internet, the cost of accessing vast amounts of information has been drastically reduced, while the volume of information supplied has increased significantly. Thus, it is logical to assume that most investors are regular internet users (Aouadi et al., 2013), and it can be expected that the volume of internet searches is a reliable proxy for measuring investors' attention to a stock. In addition to classic proxies that indirectly measure investors' attention, Ginsberg et al. (2009) introduced a method for directly measuring attention using a modern database system. Cheng et al. (2021) also measured attention

directly using Baidu search volume, which is specific to the Chinese market. Google's Search Volume Index (SVI) is the latest and most widely accepted proxy of investors' attention, which shows the search intensity of a selected keyword relative to the total search volume in specific periods and locations (Tantaopas et al., 2016).

The Mechanism of Investors' Attention Effect on Stock Liquidity

According to the Efficient Market Hypothesis, stock prices incorporate all available information as soon as it becomes public. However, this assumption relies on the idea that every investor has unlimited attention to consume all information, which is not realistic. Attention is a "scarce cognitive resource" (Kahneman, 1973) and, in reality, no individual economic agent can achieve a strong form efficiency condition. As a result, this may weaken the Efficient Market Hypothesis and raise questions about whether market prices truly reflect all available information (Ahmad, 2022; Foroghi & Rahrovi Dastjerdi, 2015; Takeda & Wakao, 2014). Today's advanced technology provides investors with a wealth of information, making it challenging to allocate attention to all available information. Therefore, investors tend to focus only on assets that are beneficial to them and ignore unappealing assets. Consequently, securities that receive more attention tend to reflect more information and are more consistent with the Efficient Market Hypothesis (Vozlyublennaia, 2014).

Merton (1987) was one of the first studies to demonstrate that investor attention plays a role in determining security prices. This finding has since been supported by other studies, including Sims (2003), Hirshleifer and Teoh (2003), Peng and Xiong (2006), Barber and Odean (2008), Da et al. (2011), Takeda and Wakao (2014), Swamy et al. (2019), and Cheng et al. (2021). However, the precise impact of information and investor attention on market equilibrium and efficiency remains unclear. While Vozlyublennaia (2014) argues that information can lead to a more efficient market, Da et al. (2011) suggest that increased attention can create additional noise and thus decrease market efficiency. In contrast to traditional asset pricing models based on the efficient market hypothesis, two alternative hypotheses have been proposed that focus on the relationship between investor attention and stock prices. The first is the "Investor Recognition Hypothesis" proposed by Merton (1987), which suggests that an increase in investor attention towards a firm leads to an increase in its stock price and liquidity. The second is the "Price Pressure Hypothesis" or "attention theory" proposed by Barber and Odean (2008), which similarly posits that an increase in investor attention leads to a temporary increase in stock price. However, this effect is not necessarily indicative of an increase in the firm's underlying value. Therefore, an initial increase in stock price due to an increase in search frequency is likely to be followed by a price reversal, as noted by Adachi et al. (2017).

The "investor recognition hypothesis" (Merton, 1987) asserts that investors possess varying levels of information and attention regarding a company, leading to different investment decisions. Consequently, companies with lower investor recognition experience higher capital costs, as the stock prices of these firms do not reflect their true value due to a lack of investor attention and awareness. This hypothesis also suggests that investors may only recognize a company's true value after a significant delay. Likewise, the "price pressure hypothesis" (Barber & Odean, 2008) proposes that institutional investor trades can temporarily influence prices and cause stocks to deviate from their intrinsic values. This hypothesis indirectly suggests that retail investors may struggle to accurately evaluate a stock's fundamental value because they do not have access to the same level of financial information as professional investors. When buying a stock, retail investors face a challenging search problem as there are thousands of common stocks to choose from, and there are limits to the amount of information that we can process. Consequently, retail investors typically seek out and purchase stocks that capture their attention, and stocks that attract investor attention usually generate excess returns and high trading volumes.

Overall, the literature suggests that retail investor attention can impact stock liquidity in at least three ways. Firstly, through the availability of information on the internet and online platforms (Barber & Odean, 2008; Tumarkin & Whitelaw, 2001), as retail investors often rely on social media and other online platforms to share information and opinions about stocks, which can affect the decisions of other investors and impact liquidity. Secondly, through herding behavior, as retail investors may be influenced by the decisions of other investors and concentrate their trades on certain stocks (Galariotis et al., 2016; Vo & Phan, 2019). This can also impact liquidity positively. Thirdly, through investor sentiments, as retail investor attention is often driven by emotions rather than rational considerations, leading to increased trading and price volatility that can impact liquidity (Baker & Wurgler, 2007). Accordingly, the following hypothesis is proposed:

Hypothesis 1: In the short term, retail investor attention has a positive impact on stock liquidity.

Although retail investor attention can increase stock liquidity in the short term, its effect is likely to be temporary and diminish over longer time horizons as other market players become more informed and market efficiency incorporates new information. In less efficient markets, retail investor attention may initially increase liquidity, but over time, this effect could turn negative as the market adjusts to new information. In more efficient markets, the impact of retail investor attention on liquidity may be less significant and dissipate more quickly. Therefore, Hypothesis 2 states:

Hypothesis 2: As the time horizon expands, the positive effect of retail investor attention on stock liquidity gradually weakens and ultimately reverses.

In this study, we define short-term, medium-term, and long-term time horizons as daily, weekly, and monthly periods, respectively. Figure 1 illustrates the theoretical foundations and mechanisms underlying the effect of retail investor attention on stock liquidity.

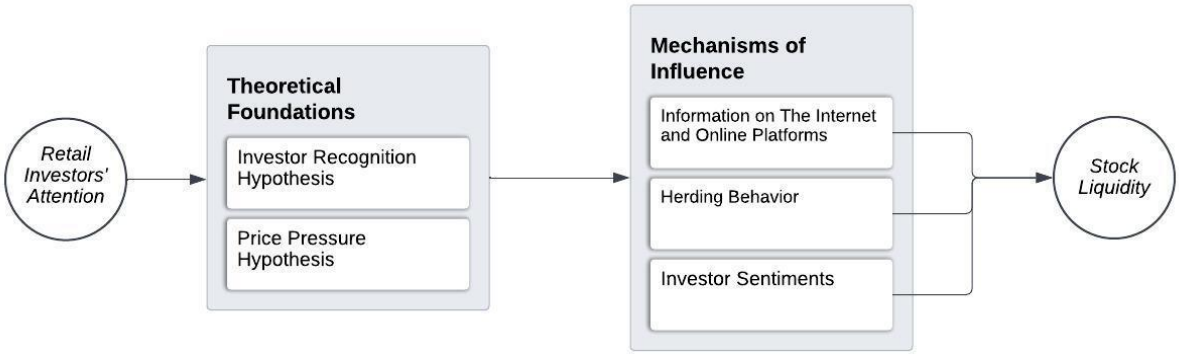


Figure 1. The theoretical foundations and mechanisms underlying the effect of retail investor attention on stock liquidity

Sample selection and data sources

In this study, we used the screening method for sampling. Our sample consists of firms listed on the Tehran Stock Exchange (TSE) from 2012 to 2022, selected based on specific criteria. Firstly, their fiscal year-end must coincide with the end of the Iranian calendar year for comparability. Secondly, all necessary information must be available to calculate research variables. Thirdly, the selected companies must not be banks or financial intermediaries due to the specific nature of their operations and assets. Lastly, the sample companies must have at least 2,000 trading days during the study period to ensure sufficient data for analysis. We determined this minimum threshold through a trial-and-error process of testing different sample sizes, as fewer trading days would decrease the reliability of statistical methods, and selecting too many trading days would lead to a significant drop in the sample size. Based on these criteria, we selected a total of 111 companies from the firms listed on the TSE. Table (1) provides more details on the sample selection process.

Table 1. Sample selection

Company	Number	Number
Total firms in TSE until the end of 2022.		409
Firms listed in TSE after March 2012	43	
Firms in financial, leasing, investment, banking, and insurance industries	145	
Firms with fiscal year-ends that differ from the end of the Iranian calendar year	48	
Firms without sufficient stock price data	4	
Firms with less than 2000 trading days in 2012 to 2022	58	
Total number of removed firms		(298)
Final sample		**111**

The necessary data for calculating variables and conducting research models were obtained from the official website of the TSE[†] and the Tehran Securities Exchange Technology Management Co[‡] website. To analyze the research data and execute models, Excel, Python, and Eviews software were used.

Research Variables

Dependent variable (stock liquidity)

To accurately measure the dynamic changes in stock liquidity, we used effective spreads daily, as suggested by Ding and Hou (2015), Jiang et al. (2017), and Cheng et al. (2021) as follows:

(1):

$$Spread = \frac{|Price - (Ask + Bid)/2|}{(Ask + Bid)/2}$$

The Spread represents stock liquidity and the Price reflects the closing stock price each day. The Ask and Bid prices are the lowest suggested buying price and the highest suggested selling price on each day, respectively. For time horizons longer than one day (such as weekly or monthly), the spread is calculated as the mean of the daily spreads during that period. When the bid and ask prices are closer to each other, the numerator of the fraction decreases while the denominator increases. This causes the spread value to decrease, indicating greater stock liquidity.

Independent variable (Retail Investor Attention)

To calculate retail investor attention on a daily basis, we used both an indirect index and a direct index. Following the approach of Grinblatt and Keloharju (2000), Barber and Odean (2008), and Cheng et al. (2021), we computed the net buy of retail investors as an indirect index of retail investor attention as follows:

[†] https://tse.ir
[‡] http://www.tsetmc.com

(2):

$$NetBuy_{i.t}=\frac{Buy_{i.t}-Sell_{i.t}}{Buy_{i.t}+Sell_{i.t}}$$

Where NetBuy is the net purchase of retail investors, and Buy and Sell are the values of retail investor purchases and sales for stock i on day, week, or month t. For longer periods than a day, this variable represents the mean of daily net buys in the week or month. A higher value for this variable indicates greater attractiveness for the stock and more attention from retail investors on that day.

In addition to the NetBuy index, we also used the Google Search Volume Index (GSVI) in the Google Trends service as a direct index of retail investor attention which is described in the sensitivity analysis section.

Control variables

By prior research (Cheng et al., 2021; Chordia et al., 2008; Grullon et al., 2004), we incorporated the following control variables: firm size (logSize), stock closing price (logClsp), daily price volatility (logVolat), and the number of years a firm has been listed on the TSE (logAge). Following standard practice in previous studies, we applied logarithmic transformations to these control variables to address key analytical considerations. First, taking the log normalizes the data, reducing skewness and minimizing the influence of extreme values—an important adjustment given the typically wide range of values for firm size, stock prices, and firm age. Second, the logarithmic transformation allows for a more intuitive interpretation of results in terms of percentage changes, aligning with the scale of these variables and facilitating clearer economic insights. Finally, using logs stabilizes variance, enhancing the reliability of our model estimations and contributing to the overall robustness of our findings.

Methodology

To examine the first hypothesis, we employed a regression model as shown below:

(3):

$$D.Liq_{i.t}=\beta_0+\beta_1 D.Attention_{i.t}+\sum_k \beta_k D.Controls_{k.i.t}+\varepsilon_{i.t}$$

In equation (3), $D.Liq_{i.t}$ represents the daily stock liquidity, which is calculated using the Spread variable. $D.Attention_{i.t}$ represents the daily level of retail investor attention, which is calculated using the NetBuy variable. $\sum_k Y_k D.Controls_{k.i.t}$ represents a set of control variables daily. To test the first hypothesis, we will examine whether the β1 coefficient is positive and significant after running equation (3). If it is, we will not reject the first hypothesis. To test the second hypothesis, we will run equation (3) every week (using the prefix W for the variables) and every month(using the prefix M for the variables). We will then compare the β1 coefficient in the weekly and monthly models with the coefficient in the daily model and analyze the results. We expect the β1 coefficient in the weekly model to be smaller than the coefficient in the daily model, and we also expect the β1 coefficient in the monthly model to be smaller than those in the weekly and daily models.

Additionally, we will use another approach based on the coefficient of the NetBuy variable's lags to test the second hypothesis.

Results

Descriptive statistics

Table (2) presents the descriptive statistics of the study variables.

Table 2: Descriptive statistics of study variables

Variables		Mean	Median	Maximum	Minimum	Standard Deviation	Observations
Stock Liquidity	D.SPREAD	0/0125	0/0094	0./0516	0/0042	0/0110	228265
	W.SPREAD	0/0129	0/0102	0/4075	0/0000	0/0099	54731
	M.SPREAD	0/0127	0/0106	0/0438	0/0032	0/0074	12892
Retail investors Net buy	D.NETBUY	-0/0317	0/0000	0/8087	-0/9125	0/2154	234634
	W.NETBUY	-0/0301	0/0000	1/0000	-1/0000	0/1822	54731
	M.NETBUY	-0/0288	-0/0031	0/2960	-0/4862	0/1104	12891
Firm Size	D.SIZE	12/6033	12/4818	14/8679	11/0753	0/7978	234660
	W.SIZE	12/5952	12/4512	15/6822	10/4434	0/8505	54731
	M.SIZE	12/5813	12/4458	14/8566	11/0499	0/7997	12892
Stock Closing Price	D.CLOSE	3/7867	3/7287	4/9976	2/8819	0/4730	234670
	W.CLOSE	3/7892	3/7277	5/6647	2/5865	0/4980	54731
	M.CLOSE	3/7823	3/7216	5/0015	2/8796	0/4718	12894
Firm Age	D.AGE	14/4191	14/5611	20/8388	3/6361	3/6088	234691
	W.AGE	14/1383	14/3962	20/9811	0/0188	4/0277	54731
	M.AGE	14/3015	14/4166	20/7500	3/7500	3/5975	12844
Stock Price Volatility	W.VOLAT	260/8308	68/4502	24375/5000	0/0000	689/1005	54731
	M.VOLAT	587/2147	202/8216	7681/6870	2/9154	985/9465	12892

In analyzing the descriptive statistics, there are three points to consider. Firstly, outliers were excluded for each research variable. Additionally, since the weekly and monthly horizon variables represent the average of these variables daily, the descriptive statistics of each variable are not the same across different time horizons (daily, weekly, and monthly). Secondly, the average of retail investors' net buy is negative in all three horizons. It should be noted that institutional investors play a critical role in daily share transactions, and due to their high liquidity, they usually trade on large scales, which significantly affects daily stock transactions. Moreover, based on the findings of Cheng et al.'s (2021) research, institutional traders tend to trade against retail investors' net buy, which results in a negative average of retail investors' net buy. However, this does not necessarily imply that all observations of this variable are negative. Thirdly, it is important to note that the Volat variable has only been presented on weekly and monthly scales due to the limited data available on a daily scale and the lack of data for smaller timeframes than a day in the Iranian capital market.

Correlation Analysis

Table (3) presents the Pearson correlation coefficient between the research variables in three different time horizons. The correlation coefficient is a key measure used to determine the presence and strength of the relationship between two or more variables. As shown in the table, the correlation coefficient between stock liquidity and retail investors' net buy on a daily time horizon is 0.023, indicating a positive correlation between these two variables. On a weekly horizon, the correlation coefficient is 0.0095, which is also positive but weaker than the daily correlation. Finally, the monthly correlation between these variables is -0.0191, indicating a negative relationship between retail investors' net buy and stock liquidity.

Table 3: Pearson Correlation Between Research Variables

		SPREAD	NETBUY	SIZE	CLOSE	AGE	
Daily Horizon	SPREAD	1					
	NETBUY	0/0230***	1				
	SIZE	-0/0126***	-0/1167***	1			
	CLOSE	0/1321***	-0/0613***	0/4863***	1		
	AGE	-0/0026	0/0410***	0/2296***	0/3539***	1	
Weekly Horizon		SPREAD	NETBUY	SIZE	CLOSE	AGE	VOLAT
	SPREAD	1					
	NETBUY	0/0095**	1				
	SIZE	-0/0252***	-0/1221***	1			
	CLOSE	0/1655***	-0/0691***	0/5084***	1		
	AGE	-0/0127***	0/0411***	0/2489***	0/3062***	1	
	VOLAT	0/0445***	0/0482***	0/2748***	0/5234***	0/1892***	1
Monthly Horizon		SPREAD	NETBUY	SIZE	CLOSE	AGE	VOLAT
	SPREAD	1					
	NETBUY	-0/0191**	1				
	SIZE	-0/0106	-0/1848***	1			
	CLOSE	0/1963***	-0/1135***	0/4942***	1		
	AGE	-0/0255***	0/0600***	0/2545***	0/3408***	1	
	VOLAT	-0/1125***	0/0523***	0/3681***	0/6756***	0/3310***	1

Regression Results

To account for the impact of industry heterogeneity over time and to address potential issues arising from the possible exclusion of important time-varying firm characteristics, we employed the two-way fixed effects regression for all of our research models. Additionally, we utilized generalized least squares (GLS) to control for variance heteroskedasticity effects. To address the impact of serial correlation on the regression, we used the "coefficient covariance method" to calculate robust residuals. We also checked for multicollinearity among explanatory variables using the Variance Inflation Factor method. As the VIF value for all variables in all models was less than 5, multicollinearity is not a concern.

Hypothesis 1. The results of the first hypothesis test, using Model (3) and a daily time horizon, are presented in Table (4). The findings suggest a positive and significant effect of retail investors' attention (D.NetBuy) on stock liquidity in the short term. Therefore, we can conclude that the first hypothesis is supported and not rejected."

Table 4: Results of Model (3) Implementation over the Daily Time Horizon

$$D.Liq_{i.t} = \beta_0 + \beta_1 D.Attention_{i.t} + \sum_k Y_k D.Controls_{k.i.t} + \varepsilon_{i.t}$$

Variable		Coefficient	SE	t-statistic	Probability	VIF
Intercept	β_0	-0/0300	0/0120	-2/4912	0/0142	
Attention	D.NETBUY	0/0026	0/0002	10/6251	0/0000	1/0195
Firm Size	D.SIZE	0/0006	0/0009	0/6795	0/4982	1/3309
Closing Price	D.CLOSE	0/0015	0/0006	2/3912	0/0185	1/4264
Firm Age	D.AGE	0/0019	0/0002	9/1688	0/0000	1/1554
F-Statistic		17/9272		R^2		0/1777
Probe F-Statistic		0/0000		Adj R^2		0/1678

Hypothesis 2. Hypothesis 2 proposes that the positive effect of retail investor attention on stock liquidity weakens and ultimately reverses as the time horizon expands. We employed two approaches to test this hypothesis. The first approach involved analyzing daily, weekly, and monthly models without considering the lags of ATTENTION. The second approach involved lag analysis of ATTENTION at each time horizon using charts. To confirm the hypothesis using the first approach, we expected the β_1 coefficient in the weekly model to be smaller than that in the daily model, and the β_1 coefficient in the monthly model to be smaller than that in both the weekly and daily models. The second approach involved examining the trend of lags in each model. If the trend starts positive, then decreases, and eventually becomes negative, then we reject the null hypothesis and support the second hypothesis.

Results for the weekly and monthly models are presented in Tables (5) and (6), respectively, using Model (3). The coefficients for the retail investors' attention variable (W.NetBuy and M.NetBuy) are 0.0019 and 0.0015, respectively, indicating a significant and downward effect on stock liquidity over longer time horizons. Hence, the first approach confirms hypothesis 2.

The relatively small coefficient values in our model can be justified given the nature and scale of the independent variables and the context of stock liquidity analysis. Logarithmic transformations applied to control variables naturally scale down their values, often resulting in smaller coefficients without diminishing their explanatory power. Additionally, while the coefficients appear small, they reflect incremental effects on liquidity, which is typically sensitive to even minor changes in variables like firm size, volatility, and stock price. Moreover, an adjusted R-squared of approximately 20% is consistent with similar studies analyzing the effects of investor attention on stock liquidity, particularly in models where liquidity is influenced by multiple factors beyond those captured by our control variables. This R-squared value suggests our model captures a meaningful portion of liquidity variation while acknowledging that liquidity is also driven by broader market dynamics and other unobserved factors.

To simplify the analysis of hypothesis 2 using the first approach, we compared the coefficients of the retail investors' attention variable in these three-time horizons in Figure (2). The downward trend of these coefficients between these time horizons is clearly visible in this figure.

Table (5): Results of model (3) implementation over the weekly time horizon

$$W.Liq_{i.t} = \beta_0 + \beta_1 W.NETBUY_{i.t} + \sum_k Y_k W.Controls_{k.i.t} + \varepsilon_{i.t}$$

Variable		Coefficient	SE	t-statistic	Probability	VIF
Intercept	β_0	0/0239	0/0043	5/5178	0/0000	
Attention	W.NETBUY	0/0019	0/0006	2/8957	0/0046	1/0315
Firm Size	W.SIZE	-0/0017	0/0003	-5/5213	0/0000	1/3834
Closing Price	W.CLOSE	0/0033	0/0004	7/1773	0/0000	1/7807
Firm Age	W.AGE	-0/0007	0/00066	-1/0594	0/2917	1/1256
Price Volatility	W.VOLAT	-0/0008	0/00019	-4/2939	0/0000	1/3927
F-Statistic		27/9314		R2		0/2119
Probe F-Statistic		0/0000		Adj R2		0/2043

Table (6): Results of model (3) implementation over the monthly time horizon

$$M.Liq_{i.t} = \beta_0 + \beta_1 M.NETBUY_{i.t} + \sum_k Y_k M.Controls_{k.i.t} + \varepsilon_{i.t}$$

Variable		Coefficient	SE	t-statistic	Probability	VIF
Intercept	β_0	0/0216	0/0011	19/0474	0/0000	
Attention	M.NETBUY	0/0015	0/0004	3/1575	0/0016	1/0842
Firm Size	M.SIZE	-0/0015	0/0008	-18/9575	0/0000	1/3802
Closing Price	M.CLOSE	0/0030	0/00015	19/9049	0/0000	2/1912
Firm Age	M.AGE	-0/0008	0/00019	-4/3070	0/0000	1/1790
Price Volatility	M.VOLAT	-0/0004	0/00068	-5/7765	0/0000	1/9402
F-Statistic		32/3865		R2		0/2571
Probe F-Statistic		0/0000		Adj R2		0/2491

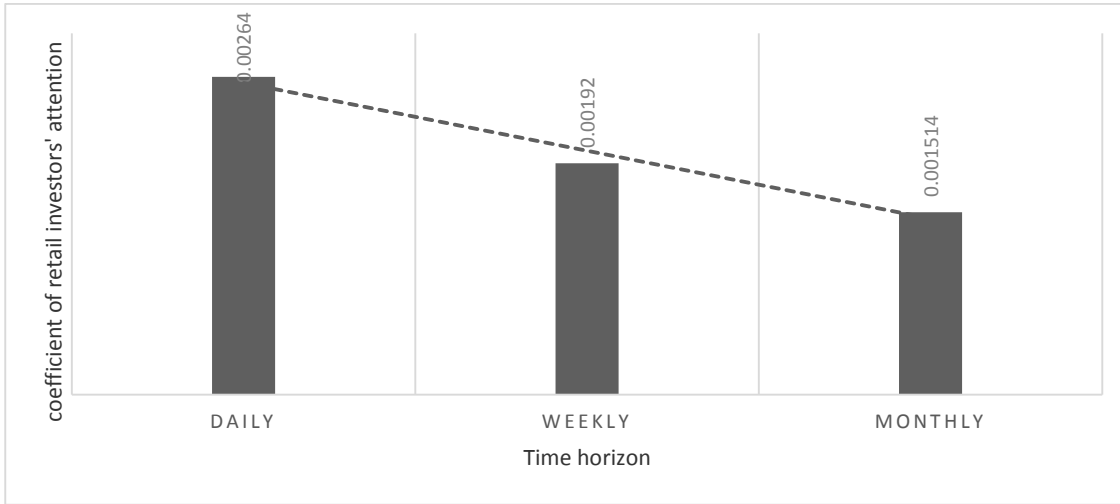


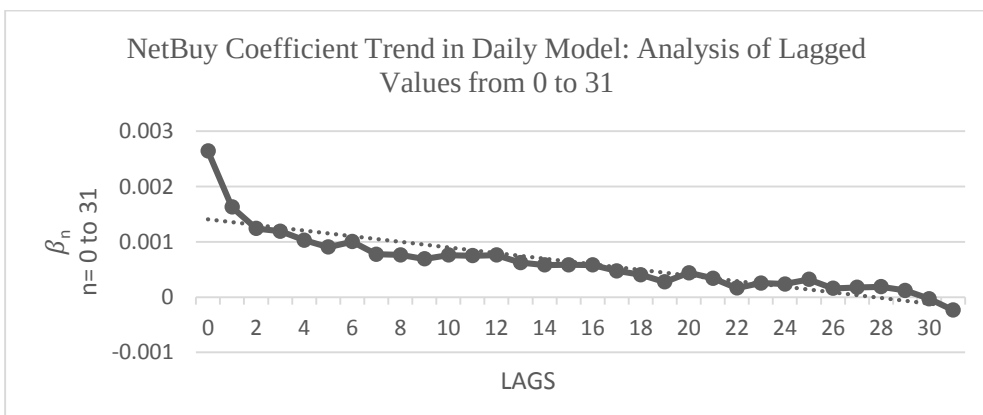
Figure 2: The decreasing trend of the coefficient of retail investors' attention as the time horizon expands

To test hypothesis 2 using the second approach, the chart of lagged coefficients for the NetBuy variable across daily, weekly, and monthly time horizons is presented simultaneously in figure (2).

Based on the daily model chart shown in Figure (3), the NetBuy coefficient exhibits a decreasing trend from Lag0 to subsequent lags and eventually becomes negative at Lag30. It is noteworthy that immediately after Lag0 (present-day), as we move toward Lag1, this coefficient significantly decreases and almost halves. Therefore, in this case, it can be concluded that retail investors' attention has the greatest positive impact on stock liquidity in the short term. The weekly model chart in Figure (3) also demonstrates a similar decreasing trend in the net buy coefficient of retail investors, which becomes negative at Lag5. Finally, the monthly model chart in Figure (3) shows that the decreasing trend continues from Lag0 to Lag1 and eventually becomes negative in the first month (Lag1).

The daily, weekly, and monthly model charts in Figure (3) demonstrate that the lag results of each model are largely consistent with the other models. Specifically, the trend of the NetBuy coefficient is decreasing in all three-time horizons, and the time frames in which this coefficient changes direction are almost the same. For instance, in the daily time horizon, the NetBuy coefficient changes direction at Lag30 (approximately equivalent to one month), in the weekly time horizon, it changes direction at Lag5 (equivalent to 35 days or about one month), and in the monthly time horizon, it changes direction at the first lag (equivalent to 30 days). Therefore, it can be concluded that the positive effect of retail investors' NetBuy on stock liquidity reverses at similar time frames across all three-time horizons.

Based on the results obtained from the second approach for testing the second hypothesis, it was observed that the positive effect of retail investors' attention on stock liquidity weakened and eventually reversed as the time horizon expanded. Therefore, the second hypothesis was not rejected using this approach as well.



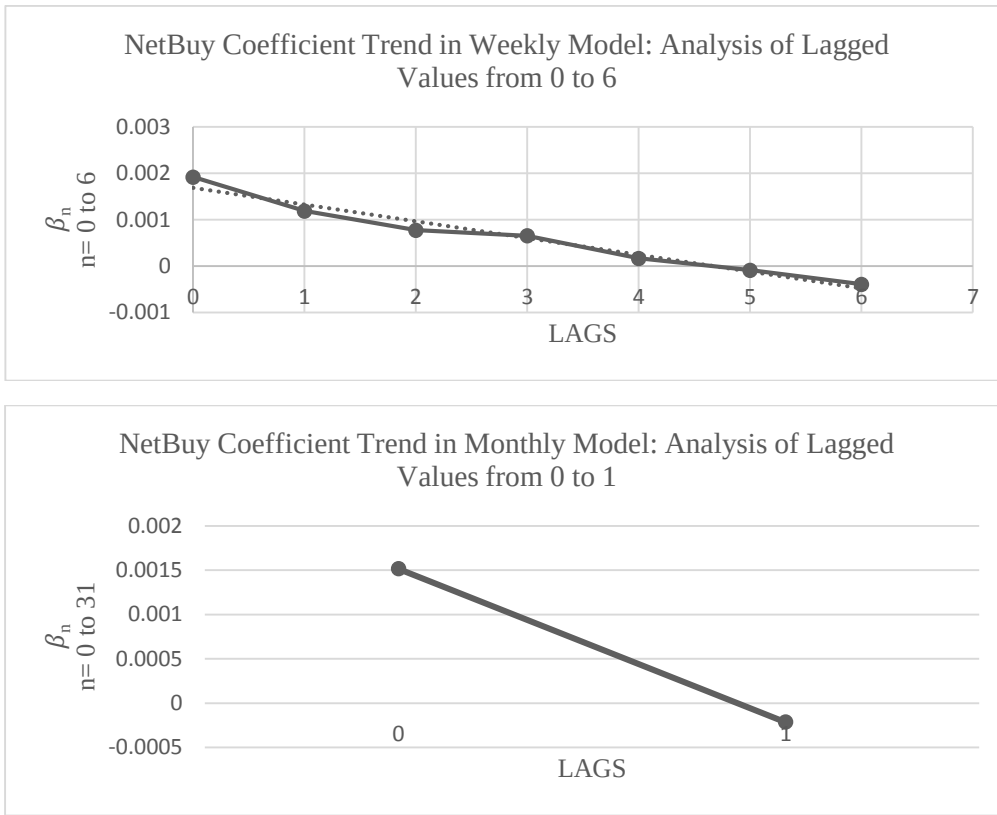


Figure 3: Lagged values for NetBuy coefficients in different time horizons

Sensitivity analysis

To further investigate the research questions, this section tested the hypotheses using the Google Search Volume Index (GSVI) in the Google Trends service as an additional proxy for measuring retail investors' attention. This approach has been used in previous studies, such as Tang and Zhu (2017), Swamy et al. (2019), Ding and Hou (2015), and Aouadi et al. (2013). The results of these tests are presented below.

The Google Trends index is one measure of retail investors' attention and enables monitoring of search trends for specific keywords, topics, and phrases over specific periods. Institutional investors typically have access to extensive and specialized information resources, making it unlikely they would use Internet searches for stock analysis and financial decision-making. However, retail investors often have limited access to information resources due to financial constraints and other limitations, making the Google Trends index a potentially significant reflection of "retail investors' attention". One limitation of using the Google Trends index is that daily frequency data are only available for the past 90 days, whereas weekly data are available for a longer period. To address this limitation and create daily data for periods longer than 90 days, we developed a Python code to automatically download daily data for all stocks analyzed between 2012 and 2022. We followed the methodology of Da et al. (2011), Takeda and Wakao (2014), and Tang and Zhu (2017) by using the company stock symbol instead of its name to measure investor attention from the Google Trends index. This approach is less ambiguous as searching for a stock using its symbol is more precise (Da et al., 2011). Moreover, using a stock symbol instead of a company name increases the likelihood that the user is an investor rather than someone searching for other company information, such as products (Aouadi et al., 2018). It can be argued that a person who searches for a stock symbol has their attention focused on that particular stock.

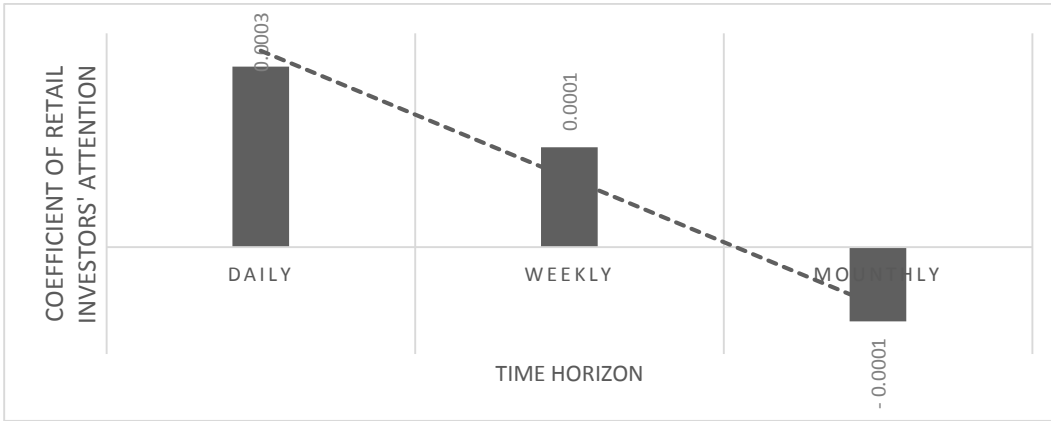


Figure 4: The decreasing trend of the coefficient of retail investors' attention (based on Google Trends) in three different time horizons

Table 7: Results of implementing model (3) using the Google Trends index for different time horizon

$$D.Liq_{i.t} = \beta_0 + \beta_1 D.GTRENDS_{i.t} + \sum_k Y_k D.Controls_{k.i.t} + \varepsilon_{i.t}$$

Variable		Coefficient	SE	t-statistic	Probability	VIF
Intercept	β_0	0/0528	0/0053	9/8762	0/0000	
Retail Investors' (Google Trends)	D.GTRENDS	0/0003	0/0001	2/5813	0/0164	1/2529
Firm Size	D.SIZE	-0/0027	0/0003	-8/0285	0/0000	1/2615
Closing Price	D.CLOSE	-0/0010	0/0003	-2/8622	0/0086	1/4219
Firm Age	D.AGE	-0/0006	0/0006	-0/9770	0/3383	1/4323
F-Statistic		7/2281		R^2		0/2815
Probe F-Statistic		0/0000		Adj R^2		0/2426

$$W.Liq_{i.t} = \beta_0 + \beta_1 W.GTRENDS_{i.t} + \sum_k Y_k W.Controls_{k.i.t} + \varepsilon_{i.t}$$

Variable		Coefficient	SE	t-statistic	Probability	VIF
Intercept	β_0	0/0504	0/0018	26/7762	0/0000	
Retail Investors' (Google Trends)	W.GTRENDS	0/0001	0/00005	1/9949	0/0461	1/3323
Firm Size	W.SIZE	-0/0026	0/0001	-21/5529	0/0000	1/3262
Closing Price	W.CLOSE	-0/0009	0/0001	-4/8520	0/0000	1/7980
Firm Age	W.AGE	-0/0005	0/00016	-3/1220	0/0018	1/1310
Price Volatility	W.VOLAT	0/0009	0/00015	5/7496	0/0000	1/6324
F-Statistic		16/8187		R^2		0/4551
Probe F-Statistic		0/0000		Adj R^2		0/4281

$$M.Liq_{i.t} = \beta_0 + \beta_1 M.GTRENDS_{i.t} + \sum_k Y_k M.Controls_{k.i.t} + \varepsilon_{i.t}$$

Variable		Coefficient	SE	t-statistic	Probability	VIF
Intercept	β_0	0/0571	0/0067	8/4760	0/0000	
Retail Investors' (Google Trends)	M.GTRENDS	-0/0001	0/0002	-0/4816	0/6344	3/9250
Firm Size	M.SIZE	-0/0029	0/0004	-6/7849	0/0000	1/8245
Closing Price	M.CLOSE	-0/0007	0/0005	-1/5722	0/1290	2/1593
Firm Age	M.AGE	-0/0009	0/00057	-1/5872	0/1255	4/9350
Price Volatility	M.VOLAT	0/0007	0/00006	11/3633	0/0000	1/1881
F-Statistic		29/3749		R^2		0/5796
Probe F-Statistic		0/0000		Adj R^2		0/5599

Table (7) presents the results of implementing model (3) using the Google Trends index in place of the NetBuy index for three different time horizons. The coefficient of the Google Trends variable for daily, weekly, and monthly time horizons were 0.0003, 0.0001, and -0.0001, respectively. These coefficients suggest a decreasing trend of the effect of retail investors' attention on stock liquidity. This finding is consistent with the results obtained from using the NetBuy variable as the retail investors' attention index. Therefore, it can be concluded that the first and second hypotheses of the research remained robust and unchanged regarding the change in the retail investors' attention index. The coefficients of the retail investors' attention variable (based on Google Trends) for the three different time horizons are compared in Figure (4).

Additionally, Figure (5) displays the test of the second hypothesis using the Google Trends index as the second approach. The figure clearly shows a decrease in the coefficient of the retail investors' attention variable from the first lag to the subsequent lags. As a result, the second hypothesis was not rejected with the second approach.

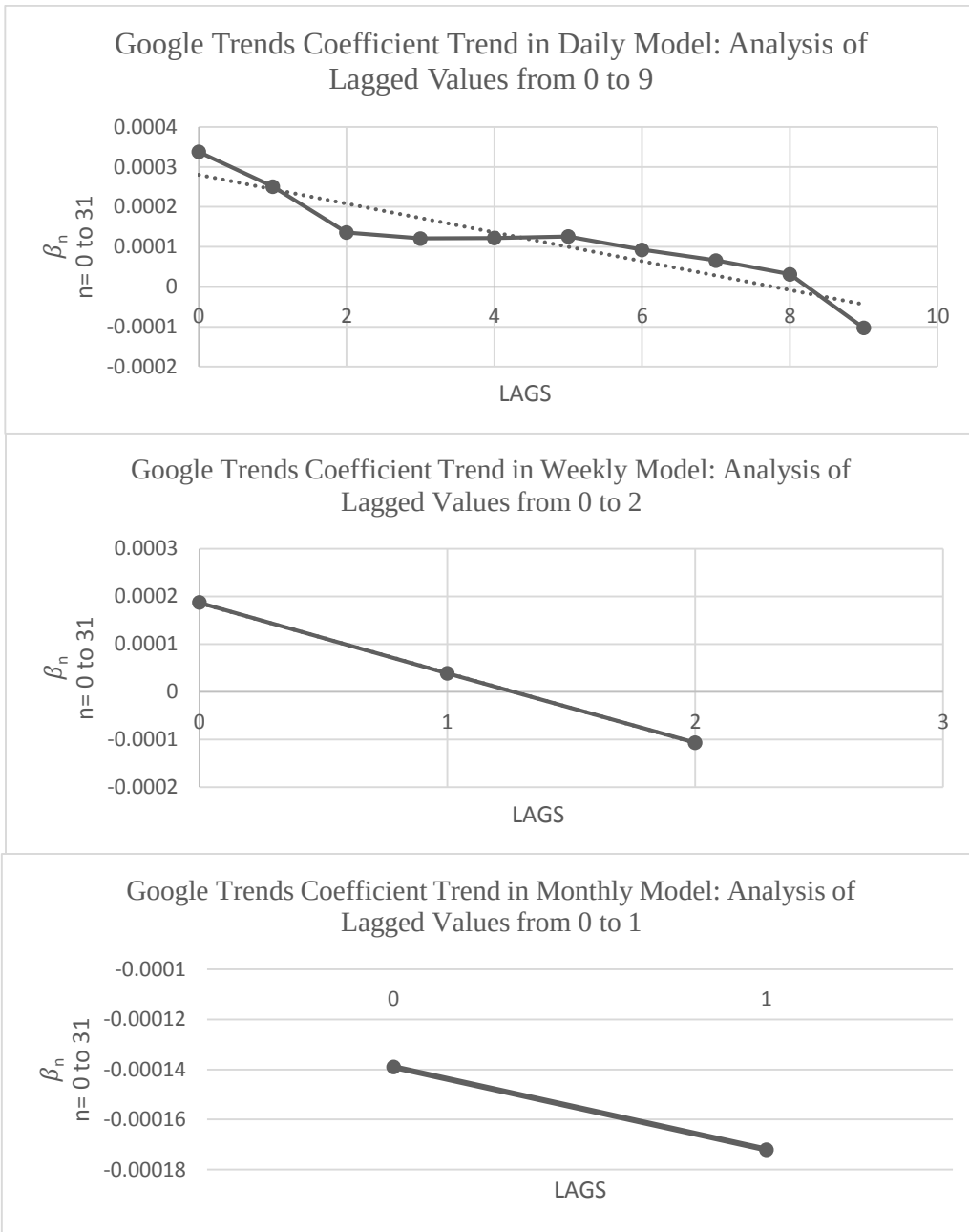


Figure 5: Lagged values for Google Trends Index coefficients in different time horizons

Overall, the sensitivity analysis indicates that the results of testing the research hypotheses were robust to changes in the measurement index of retail investors' attention.

Conclusion and Recommendations

This study aimed to analyze the effect of retail investor attention on stock liquidity in the TSE across different time horizons. The findings indicate a positive impact of retail investors' attention on stock liquidity in the short term, which gradually weakens in the medium term and ultimately reverses in the long term. Notably, these results remain robust even when using different proxies to measure retail investor attention.

Our research underscores the importance of retail investors in determining stock liquidity and highlights their crucial role in capital markets. Our findings demonstrate that stock liquidity is essential for companies operating in capital markets and is regarded as a key indicator of market development. Therefore, company managers, policymakers, and supervisors need to recognize all factors that can significantly impact stock liquidity, including the role of retail investors. In emerging markets, there may be a misconception that institutional shareholders, due to their substantial liquidity and capacity for large-scale trades, should be the primary focus, while retail investors require less attention or support.

However, our research demonstrates the significant impact of retail investors and their attention on stock liquidity. Ignoring their role in the capital market would be a significant oversight; thus, acknowledging the importance of retail investors is vital for the growth and development of the market.

In today's digital age, the internet and social media have emerged as influential platforms for retail investors and their sentiment. Unlike institutional shareholders, retail investors lack privileged access to news and resources, making them more susceptible to news and rumors circulating on social media. Company managers should monitor information about their companies on the internet and social media platforms to address any misinformation proactively. Similarly, policymakers and supervisors can protect retail investors' rights by implementing suitable regulations, legal requirements, and transparency measures for companies operating in the capital market. Such policies should require companies to provide clear and transparent information on their financial status, stock prices, and other pertinent data. Furthermore, companies could be encouraged to hold informational sessions to address rumors about the company or stock price movements, helping to stabilize retail investor sentiment. While retail investors' attention can improve short-term stock liquidity, as shown in this study, these effects are short-lived and ultimately reverse. Consequently, policymakers should work to strengthen retail investors' financial literacy to help them manage emotional trading behavior and make informed decisions regarding risk and capital management. This approach may reduce periodic, adverse fluctuations in stock liquidity and increase market efficiency. Additionally, policymakers should implement measures to ensure the integrity of information shared by companies and to prevent insider trading and other forms of market manipulation, fostering a fair and transparent market environment and promoting investor confidence.

Future research can extend this study by examining the influence of retail investors' susceptibility to social media platforms across countries using web-mining methods to assess its impact on factors such as stock liquidity. Further research could also investigate various factors influencing retail investor attention, including political events (e.g., intergovernmental agreements or conflicts), social movements (e.g., support or boycotts of particular products), international news (e.g., reports of conflicts abroad), or crises (e.g., the COVID-19 pandemic). Finally, we suggest that future researchers explore how media coverage influences retail investor attention and trading behavior, along with its effects on market efficiency and price discovery.

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