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Effects of investor attention on Brazilian stock market liquidity

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Abstract

This study examines the effects of investor attention on the liquidity of the Brazilian stock market. Beyond traditional measures, liquidity is analyzed through informational and behavioral aspects. Principal Component Analysis (PCA) captures its multidimensional nature, while the Autoregressive Distributed Lag (ARDL) model evaluates short- and long-term dynamics using monthly data from 2006 to 2021. Findings show that investor attention has a significant and positive impact on liquidity, even when controlling for macroeconomic factors. The research provides novel evidence from an emerging market, where information is more heterogeneous and liquidity less stable than in advanced economies. It highlights investor attention as a determinant of liquidity and stresses the role of transparency, financial education, and equal access to information in promoting market efficiency and stability.

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1. Introduction

In financial markets, liquidity, defined as the ease with which trades can be executed (Amihud *et al*., 2005), is an important indicator of market efficiency. It affects transaction costs, expected returns, and the stability of financial systems (Chordia *et al*., 2008). Additionally, liquidity is closely linked to investor trading behavior and the rate at which information is reflected in asset prices (Kurov, 2008).

The role of limited investor attention, as first theorized by Kahneman (1973) and later expanded in the context of market phenomena such as price pressure (Barber & Odean, 2008), has garnered increasing academic interest. These theories propose that the limitations in investors' attention can lead to fluctuations in market liquidity and efficiency. However, the selection of appropriate variables to capture investor attention remains contested, with Google Trends search volume frequently employed as a proxy for retail investor attention (Takeda & Wakao, 2014; Ding & Hou, 2015; Tantaopas *et al*., 2016; De Souza *et al*., 2018; Kim *et al.,* 2019; Zhao & Zhang, 2024; *Raza et al., 2025*).

Multiple studies across various markets have suggested that retail investor attention significantly impacts stock liquidity, particularly in the short term. This effect has been documented in markets including the United States (Ding & Hou, 2015), France (Aouadi *et al.,* 2013), Japan (Takeda & Wakao, 2014), China (Fan *et al*., 2017; Yang *et al*., 2020; Cheng *et al.*, 2021; Zhao & Zhang, 2024), Brazil (De Souza *et al.,* 2018; Pereira *et al.,* 2020), and Norway (Kim *et al*., 2019), as well as in developed and emerging markets in the Asia-Pacific region (Tantaopas *et al.,* 2016; Padungsaksawasdi *et al.,* 2019). While these studies provide evidence of a short-term relationship between investor attention and liquidity, the long-term dynamics remain less understood (Cheng *et al.,* 2021).

The objective of this study is to investigate the impact of investor attention on stock market liquidity across different time horizons, with a focus on Brazil, one of the largest emerging economies in the world, using a broad market index rather than individual stocks. This study provides both theoretical and empirical contributions by analyzing how investor attention interacts with market liquidity under different market conditions, including periods of financial stress. The analysis covers a sample period from 2006 to 2021, which includes multiple crises and varying market environments. Furthermore, the robustness of the results was verified through placebo tests and additional robustness checks, reinforcing the reliability of the findings.

To address the multidimensional nature of liquidity, an aggregate measure was constructed using three different metrics: the number of securities, financial volume, and number of trades. Dimensionality was then reduced through Principal Component Analysis (PCA), and the sensitivity of this composite liquidity measure to investor attention was estimated using an autoregressive distributed lag (ARDL) model. This hybrid PCA + ARDL approach allows for the assessment of both short- and long-term relationships while controlling for macroeconomic variables, providing a robust and nuanced understanding of the attention-liquidity link.

The main results suggest that the liquidity of the Brazilian stock market is significantly influenced by investor attention. Although there are variations in the magnitudes of the short- and long-term effects, the impact remains predominantly positive even when controlling macroeconomic variables. These findings remained robust across the various tests conducted, supporting the validity of the estimated relationships.

2. Methodology

2.1 Data

The dataset covers the period from January 2006 to February 2021, with monthly frequency. The dependent variable is liquidity, a multidimensional concept that cannot be captured by a single metric. For this reason, three widely used measures in studies of the Brazilian market were selected: (i) number of securities, (ii) financial volume, and (iii) number of trades, all obtained from Economática. These series were chosen because they represent the most consistently available, long-horizon, and market-wide liquidity indicators for Brazil, ensuring comparability over time. Although alternative measures such as bid-ask spread, Amihud illiquidity, or turnover could also be used, they tend to be noisier at the monthly frequency, have shorter or less consistent coverage for the Brazilian market, and are often more sensitive to microstructure effects. By contrast, the selected indicators capture complementary dimensions of trading activity and are well suited for aggregation through PCA. All series were deseasonalized and log-transformed to mitigate peaks and extreme values, following Campbell *et al.* (1993) and Bijl *et al.* (2016).

PCA (Pearson, 1901; Hotelling, 1933) was employed to extract the first principal component from these three liquidity measures. This approach explains the covariance structure of the variables through linear combinations, reducing dimensionality and improving interpretation, particularly when dealing with interrelated variables (Johnson & Wichern, 1998). Dimensionality reduction is achieved by transforming the original dataset into a new set of variables that retains as much of the original variability as possible. Specifically, given a random vector of variables with a mean vector μ and a variance-covariance matrix Σ, a new set of variables $Y_1, Y_2, \dots, Y_p$ is identified, which are uncorrelated with each other and have variances arranged in decreasing order.

For operational purposes, each variable was standardized relative to its mean and standard deviation. Subsequently, the eigenvalues and eigenvectors of the correlation matrix were computed. Using these results, a liquidity measure for the Brazilian market was derived as a linear combination of the three variables, with the eigenvector corresponding to the highest eigenvalue serving as the weight. Consequently, the first component captures most of the variance in the data, while each subsequent component accounts for the maximum remaining variance, subject to the constraint of orthogonality to the preceding components. The first component explained approximately 68% of the total variance in the data.

The primary explanatory variable in this study is investor attention, which is proxied by search volume data from Google Trends, following prior research (Aouadi *et al*., 2013; Ding & Hou, 2015; Tantaopas *et al*., 2016; De Souza *et al*., 2018; Kim *et al*., 2019; Padungsaksawasdi *et al*., 2019; Pereira *et al*., 2020; Zhao & Zhang, 2024; Raza *et al*., 2025). This measure captures the intensity of online searches for a given term across a selected period and geographic region, with normalized values ranging from 0 to 100. A value of 100 indicates that the term reaches its highest search frequency within the chosen time frame and location, while a value of 0 indicates either no searches or a very low number of searches (Choi & Varian, 2012; Yung & Nafar, 2017). Because this research focuses on aggregate market behavior, the search term used was "Ibovespa," and the series was transformed using a logarithmic function.

An additional feature of the Search Volume Index is that conducting online search is a spontaneous action by individuals, which means it does not originate directly from financial market activities and therefore reduces concerns about endogeneity (Guzella, 2020). Da, Engelberg and Gao (2011) argue that increases in search activity often reflect investors' natural reactions to news rather than feedback from market variables. This does not compromise the use of Google Trends as a measure of attention, because these searches capture shifts in information demand. When the model includes controls for market and macroeconomic conditions, concerns about reverse causality or broader endogeneity are substantially reduced.

Several control variables were included to assess whether the impact of investor attention on stock market liquidity persisted. The covariates considered were:

- Market return (RET) is included as a proxy for investor confidence. A positive association between market return and liquidity suggests increased investor confidence, whereas a negative association indicates diminished confidence (Statman *et al*., 2006; Dhaoui & Bacha, 2017; Prates *et al*., 2014). Market return is calculated as the logarithmic return of the Ibovespa closing prices: $RET_{t,i} = ln\ (p_{t,i}/p_{t-1,i})$, where p represents the closing price.

- The interest rate (INTR) is a key monetary policy instrument used by major central banks to regulate stock market liquidity and promote stable conditions for economic growth and sustainable development (Sun & Yuan, 2021). Recent studies have demonstrated a significant negative relationship between interest rates and stock market liquidity (Brunnermeier & Pedersen, 2008; Zhang *et al*., 2019). In this study, the SELIC rate (expressed as a percentage per month) provided by the Instituto de Pesquisa Econômica Aplicada (IPEA) is utilized.

- Inflation (INF) can indirectly affect market illiquidity by driving fund outflows, depressing prices, and increasing volatility, thereby heightening stock risk (Goyenko & Ukhov, 2009). Omran and Pointon (2001) provide evidence that the inflation rate negatively impacts stock market performance, influencing both activity and liquidity in the short and long term. In this study, the Broad Consumer Price Index (IPCA), expressed as a percentage per month and provided by IPEA, is utilized.

- Monetary Base (MB). According to Fernández-Amador *et al*. (2013), an increase in the monetary base is expected to positively influence liquidity variables. Expansionary monetary policy that enlarges the monetary base increases the money supply within the economy, thereby facilitating transactions, lowering trading costs, and enhancing market liquidity, which, in turn, eases the buying and selling of assets. In this study, the average amount of currency in circulation, provided by IPEA, is used as a proxy for the monetary base. Consistent with Fernández-Amador et al. (2013), the monetary base is defined as the continuous twelve-month growth rate: $MB_t = (\frac{MB_t - MB_{t-12}}{MB_{t-12}}) * 100$.

Table I presents the descriptive statistics for the variables analyzed. The liquidity variable exhibits a mean of 0.001 and a median of -0.080, indicating an asymmetrical distribution with a greater concentration of values below the mean. The data demonstrates considerable variation, as reflected by the maximum value of 6.230 and the minimum value of -2.880. The standard deviation of 1.397 suggests moderate dispersion around the mean. Additionally, the positive skewness of 0.860 and kurtosis of 4.529 indicate a right-skewed distribution with the presence of extreme values. The attention variable has a mean of 1.025 and a median of 0.954, indicating that the values are concentrated around 1. The standard deviation of 0.319 implies moderate dispersion. The positive skewness of 0.538 suggests a slight rightward skew, while the kurtosis of 2.337 indicates a distribution relatively close to normality. Regarding the Ibovespa returns, the data show a slightly positive mean with high kurtosis and negative skewness, suggesting the presence of extreme values and a leftward skew.

Table I - Descriptive statistics and correlation matrix.

Descriptive Statistics						
Statistics	LIQ	ATE	RET	INF	INTR	MB
Mean	0.001	1.025	0.002	0.452	0.764	12.288
Median	-0.080	0.954	0.003	0.430	0.810	10.602
Maximum	6.230	2.000	0.068	1.350	0.130	47.702
Minimum	-2.880	0.602	-0.154	-0.380	1.120	2.675
Standard Deviation	1.397	0.319	0.030	0.306	0.258	8.912
Skewness	0.860	0.538	-1.123	0.442	-0.569	1.959
Kurtosis	4.529	2.337	7.582	3.740	2.733	7.495
Correlation matrix						
LIQ	1.000					
ATE	0.538	1.000				
RET	-0.105	-0.048	1.000			
INF	-0.283	-0.181	-0.057	1.000		
INTR	-0.341	-0.410	-0.068	0.112	1.000	
MB	0.149	0.614	0.047	0.072	-0.398	1.000

Note. The variables are liquidity (LIQ), investor attention (ATE), Ibovespa return (RET), inflation (INF), interest rate (INTR) and monetary base (MB). All statistics are based on 171 observations.
Source. Prepared by the authors.

The remaining variables exhibit common patterns of variation and dispersion. Each variable's mean reflects the central tendency of its distribution, while the standard deviations indicate moderate to high levels of dispersion. The skewness values range from slight left to right asymmetry, and the kurtosis values suggest distributions with heavier tails than a normal distribution, indicating the presence of extreme values in each case. The correlation matrix reveals a positive association between investor attention and liquidity. Although this correlation is moderate, it indicates a potential relationship between the two-time series, suggesting that fluctuations in liquidity may be linked to changes in investor attention and vice versa.

2.2 Estimation strategy

ARDL modeling (Pesaran & Shin, 1999; Pesaran *et al*., 2001) was employed to analyze the relationship between investor attention and stock market liquidity. This model is effective for estimating cointegration relationships and long-term equilibrium, as well as capturing both short- and long-term dynamic effects. Its advantages include applicability to variables with different orders of integration ($I(0)$ or $I(1)$), effectiveness with small samples, and the ability to determine the optimal number of lags to address issues of serial correlation and endogeneity of the regressors (Pesaran & Shin, 1999).

To implement the ARDL model, several steps are required. First, the stationarity properties of the variables need to be investigated, as the model accommodates variables integrated into mixed orders, whether they are stationary at the $I(0)$ level, at the $I(1)$ first difference, or a combination of both. This analysis can be conducted by applying and comparing the results of the Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1981), the Phillips-Perron (PP) test (Phillips & Perron, 1988), and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (Kwiatkowski *et al*., 1992).

Secondly, a bounds test is performed to assess the existence of a long-term relationship between the variables. This test involves calculating the F-statistics under the null hypothesis (H0) that no long-term relationship exists. If the F-statistics are below the critical values, the null hypothesis is not rejected, indicating no cointegration. Conversely, if the F-statistics exceed the critical values, the null hypothesis is rejected, suggesting cointegration and a long-term relationship between the variables. Thirdly, the optimal lag length for each variable must be determined using the Akaike Information Criterion (AIC) (Akaike, 1973). According to Pesaran and Smith (1995), the general ARDL model can then be constructed to explore cointegration among all the variables as follows:

$$y_t = C + \alpha T + \sum_{i=1}^{p} \theta_i y_{t-i} + \sum_{j=1}^{k} \sum_{i=0}^{q} \beta_{ji} x_{jt-i} + \mu_t \tag{1}$$

where y_t is the dependent variable, T is the time trend, $x_{jt}(j = 1, 2, \ldots k)$ represents the explanatory variables, and $p\,(p \geq 1)$ e $q\,(q \geq 0)$ denote the optimal lag lengths. For simplicity, this study assumes that the lag length is the same for all variables in x_{jt}. $\mu_t$represents the error term.

Finally, the ARDL model is transformed into an Error Correction Model (ECM) structure to incorporate both short-term dynamics and long-term equilibrium. The standard ARDL regression model provides information only on short-term parameters, which can be insufficient for exploring long-term relationships. By employing the ECM, issues such as spurious estimates resulting from non-stationary variables are addressed. Consequently, the ARDL model is reparametrized into the ARDL-ECM model. Through a simple linear transformation of equation (1) (Pesaran & Shin, 1999), the error correction version of the ARDL model is expressed as follows:

$$\Delta y_t = C_1 + \alpha' T - \varphi ECM_{t-1} + \sum_{i=1}^{p-1} \theta'_i \Delta y_{t-i} + \sum_{j=1}^{k} \sum_{i=0}^{q-1} \beta'_{ji} \Delta x_{jt-i} + \mu_t \tag{2}$$

In equation (2), the error correction term is represented with a lag period ECM_{t-1}, and φ represents the correction coefficient, which reflects the degree to which the imbalance is adjusted when the dependent variable deviates from its long-term equilibrium relationship; $\varphi > 0$ indicates a divergent adjustment, and $\varphi < 0$ a convergent adjustment.

After estimating the model, several diagnostic tests must be performed, including assessments for normality, serial correlation, heteroscedasticity, and the adequacy of the specified functional form. It is also essential to evaluate the stability of the model coefficients using the cumulative sum (CUSUM) and cumulative sum of squares (CUSUMSQ) tests (Brown *et al.*, 1975). Parameters are considered unstable if these tests fall outside the 5% critical bands, indicating potential structural breaks in the estimates. These tests are particularly important for series that may exhibit structural breaks over time. Given that the analyzed period includes crises, these tests are crucial for ensuring the reliability of the model.

A total of five models were estimated. The first model uses liquidity as the dependent variable and attention as the explanatory variable. In the subsequent models, additional explanatory variables were included one at a time, in the following order: return, inflation, interest rate, and monetary base.

3. Results and discussions

Initially, the order of integration of the series is examined to ensure that none of the variables is *I*(2), as the ARDL approach requires the variables to be either *I*(0), *I*(1), or mutually cointegrated. The ADF and PP tests assess the null hypothesis (H_0) that the series is non-stationary and integrated of order d (d > 0), *I*(1) or *I*(2), against the alternative hypothesis (H_1) of stationarity, *I*(0). In contrast, the KPSS test tests the null hypothesis (H_0) that the series is

$I(0)$ and the alternative hypothesis (H_1) that the series is $I(1)$. Table II presents the results of these tests.

Table II - Results of the ADF, PP and KPSS tests for variables in level and first difference.

	ADF (*t-stat*)		PP (*t-stat*)		KPSS (*LM-stat*)	
	In level	First difference	In level	First difference	In level	First difference
ATE	-0.639	-12.540	-0.926	-17.639	0.143	-
LIQ	-5.457	-	-8.203	-	0.356	-
RET	-9.397	-	-11.013	-	0.065	-
INF	-2.901	-	-6.715	-	0.071	-
INTR	-0.956	-3.275	-1.127	-23.933	0.320	-
MB	-1.435	-6.037	-1.360	-9.780	0.275	-

Note. The variables are liquidity (LIQ), investor attention (ATE), Ibovespa return (RET), inflation (INF), interest rate (INTR), and monetary base (MB). The appropriate lag lengths for the ADF tests are determined using Akaike's Information Criterion. Andrew's procedure was applied to calculate the bandwidths for the PP test. The critical values at the 5% level are as follows: ADF (t-stat) 5%, t-calc. = -2.876; PP (t-stat) 5%, t-calc. = -2.878; KPSS (LM-stat) 5%, t-calc. = 0.462. The statistics are based on 171 observations.
Source. Prepared by the authors.

The tests indicate the presence of $I(0)$ and $I(1)$ variables, justifying the use of the ARDL model. At this stage, each of the five models must be adjusted with the optimal number of lags for each variable. With a maximum lag order of $p = 4$, the existence of a long-term relationship between the variables was tested using the ARDL bounds test, with results presented in Table III.

Table III - ARDL bounds test for long-term relationships.

H_o: No cointegration	Computed F statistic	5% *Critical bounds*		1% *Critical bounds*	
		$I(0)$	$I(1)$	$I(0)$	$I(1)$
Model 1 – ARDL (3.4)	13.628	3.62	4.16	4.94	5.58
Model 2 – ARDL (3.4.0)	12.541	3.10	3.87	4.13	5.00
Model 3 – ARDL (3.4.0.4)	11.021	2.79	3.67	3.65	4.66
Model 4 – ARDL (3.4.0.4.1)	9.490	2.56	3.49	3.29	4.37
Model 5 – ARDL (3.4.0.2.1.1)	9.158	2.39	3.38	3.06	4.15

Source. Prepared by the authors.

The F-statistic calculated for all models exceeds the critical values at both the 5% and 1% levels. Based on this result, the null hypothesis is rejected, concluding that investor attention has a long-term impact on the liquidity of the Brazilian market. Before analyzing the short- and long-term effects, the suitability of the dynamic specification was assessed using various diagnostic tests. The Breusch-Godfrey LM test did not reject the null hypothesis of no autocorrelation. The Breusch-Pagan-Godfrey LM test did not reject the null hypothesis of no heteroscedasticity. The Jarque-Bera test confirmed the normality of the residuals, and Ramsey's RESET test did not reject the null hypothesis that polynomial terms do not improve the model fit, indicating no specification error in the regression equation. Finally, the CUSUM and CUSUMSQ tests confirmed the stability of the model coefficients, suggesting that turbulent periods, such as the 2008 financial crisis and the COVID-19 pandemic, did not affect the estimates. Therefore, the results presented in the statistical summary support the validity of all models.

Table IV - Short- and long-term estimates for ARDL models.

Panel A:	**Long-term estimates**				
Dependent variable: LIQ	Model 1	Model 2	Model 3	Model 4	Model 5
ATE	1.322***	1.275***	1.237***	1.045**	1.131**
RET		0.049***	0.047***	0.044**	0.036**

	Model 1	Model 2	Model 3	Model 4	Model 5
INF			-0.718	-0.934^{*}	-1.149^{*}
JUR				-0.810^{*}	-0.631
BM					-0.007
Panel B:		**Short-term estimates**			
Dependent variable: ΔLIQ	Model 1	Model 2	Model 3	Model 4	Model 5
$\Delta(LIQ)_{-1}$	-0.168^{**}	-0.173^{**}	-0.158^{**}	-0.046	0.011
$\Delta(LIQ)_{-2}$	-0.142^{**}	-0.162^{**}	-0.143^{**}	-0.140^{**}	-0.130^{**}
Δ(ATE)	10.134^{***}	10.024^{***}	9.637^{***}	8.866^{***}	8.960^{***}
$\Delta(ATE)_{-1}$	3.100^{***}	3.473^{***}	3.075^{***}	2.532^{**}	2.647^{**}
$\Delta(ATE)_{-2}$	3.470^{***}	3.911^{***}	3.782^{***}	3.606^{***}	3.454^{***}
$\Delta(ATE)_{-3}$	1.499^{*}	1.520^{*}	1.525^{**}	1.129^{*}	1.291^{*}
Δ(INF)			-0.189	-0.190	-0.176
$\Delta(INF)_{-1}$			0.282	0.342	0.566^{**}
$\Delta(INF)_{-2}$			-0.148	-0.153	
$\Delta(INF)_{-3}$			-0.643^{**}	-0.572^{**}	
Δ(JUR)				2.599^{**}	3.236^{***}
Δ(BM)					0.051^{**}
ECM_{-1}	-0.514^{***}	-0.516^{***}	-0.561^{***}	-0.591^{***}	-0.640^{***}
		Statistical summary			
R^2	0.682	0.697	0.722	0.745	0.7668
R^2 Ajusted	0.666	0.679	0.697	0.718	0.751
$\chi^2_{s/corr}$	0.415(0.660)	0.277(0.757)	0.086(0.917)	0.129(0.878)	0.345(0.708)
χ^2_{het}	1.417(0.193)	1.166(0.320)	0.873(0.589)	0.709(0.781)	1.018(0.440)
χ^2_{norm}	0.726(0.695)	1.133(0.567)	0.448(0.799)	0.541(0.762)	0.479(0.786)
F_{reset}	0.263(0.792)	0.763(0.446)	1.581(0.115)	1.680(0.094)	0.863(0.389)
CUSUM	Sig. 5%	Sig. 5%	Sig. 5%	Sig. 5%	Sig. 5%
CUSUMSQ	Sig. 5%	Sig. 5%	Sig. 5%	Sig. 5%	Sig. 5%

Note. The variables are liquidity (LIQ), investor attention (ATE), Ibovespa return (RET), inflation (INF), interest rate (INTR), and monetary base (MB). Δ denotes the first difference of the respective variable. Diagnostic tests are represented as follows: $\chi^2_{s/corr}$ for the Breusch-Godfrey LM test for serial correlation, χ^2_{het} for the Breusch-Pagan-Godfrey LM test for heteroscedasticity, χ^2_{norm} for the Jarque-Bera test for normality, F_{reset} for the Ramsey RESET test for regression equation misspecification, CUSUM for the cumulative sum of residuals, and CUSUMSQ for the cumulative sum of squared residuals. The error correction term (ECM-1) shows significant coefficients that indicate the speed of liquidity adjustment toward long-term equilibrium after a shock. Significant negative values suggest that liquidity deviations from long-term equilibrium are partially corrected in the subsequent period. All statistics are based on 171 observations. The summary statistics include the test statistics and their p-values in brackets. p-value: 1% = ***, 5% = **, 10% = *.
Source. Prepared by the authors.

Table IV presents the estimated short- and long-term relationships for each model. In the short term, changes in investor attention and their lags show positive and significant coefficients, indicating that increases in attention in the current and previous periods are associated with higher market liquidity. This result is consistent with previous studies (Aouadi *et al.,* 2013; Takeda & Wakao, 2014; Tantaopas *et al.,* 2016; Fan *et al*., 2017; De Souza *et al.,* 2018; Kim et al., 2019; Padungsaksawasdi et al., 2019; Yang et al., 2020; Pereira et al., 2020). Higher investor attention tends to increase trading volume (Padungsaksawasdi *et al.,* 2019), often driven by impactful news in both rising and falling markets, which attracts abnormal trading activity (Takeda & Wakao, 2014; Tantaopas *et al*., 2016). From an economic perspective, the cumulative short-term effects indicate a meaningful increase in the liquidity measures captured by the PCA factor. In the long term, attention also displays positive and significant coefficients, pointing to persistent effects on market liquidity.

Ibovespa returns in Models 2 to 5 show a positive and significant long-term impact on liquidity. This finding aligns with earlier evidence (Statman *et al*., 2006; Prates *et al.,* 2014; Dhaoui & Bacha, 2017), which reports a positive relationship between returns and liquidity associated with increased investor confidence. The magnitude of the long-term coefficients suggests that even moderate improvements in market performance coincide with perceptible gains in liquidity.

Inflation exerts a negative and significant impact on liquidity in the short term (t_{-3}) and in the long term (Model 4). This result supports theoretical expectations and is consistent with Omran and Pointon (2001). According to Goyenko and Ukhov (2009), high inflation indirectly reduces liquidity by causing fund outflows, price declines and higher volatility, all of which increase transaction costs. Economically, the long-term estimates imply that sustained inflationary pressure can materially shrink market liquidity.

Interest rates present significant coefficients with mixed signs. In the long term, the effect is negative because higher interest rates raise borrowing costs and reduce the money supply, which lowers investor optimism and trading frequency (Brunnermeier & Pedersen, 2008; Zhang *et al*., 2019). In the short term, higher rates are associated with increased liquidity, a pattern compatible with Sun and Yuan (2021), who show that the interest rate and liquidity relationship varies across time horizons and contexts. The short-term positive effect may reflect temporary reallocations following monetary announcements, while the long-term negative effect captures the restrictive influence of persistent high rates.

The monetary base shows a positive and significant short-term effect. Expansionary monetary policy increases money availability, facilitates transactions and reduces trading costs, which ultimately enhances liquidity (Fernández-Amador *et al.,* 2013). The coefficient magnitudes indicate that incremental increases in monetary supply translate into observable gains in the PCA-based liquidity measure.

Overall, the results indicate that investor attention is an important determinant of liquidity in the Brazilian market. The relationship remains robust even when macroeconomic variables are included, suggesting that attention stimulates market participation in response to news and economic conditions. Although the relatively large magnitudes observed in the attention coefficients can be partially explained by the normalization of the PCA components and by the ARDL specification in levels, these effects remain valid and reflect real patterns of market behavior, which reinforces the economic interpretation of the results. The diagnostic tests do not indicate specification problems, supporting the consistency of the findings.

3.1 Robustness tests

To assess the robustness of the relationship between attention and liquidity, we conducted additional tests considering different market regimes and levels of volatility. We created a crisis dummy (D_{crise}) that takes the value of 1 during periods considered as crises and 0 otherwise, without distinguishing specific crises. In addition, we defined a high volatility dummy (D_{vol}), which takes the value of 1 when the six-month rolling volatility is above the median of the return series in the models, and 0 otherwise. The rolling volatility was calculated as the standard deviation of returns over the six months preceding each observation. To examine whether the effect of attention on liquidity varies according to market conditions, we estimated interactions between attention and each of the dummies:

$$ATED_{Crise} = ATE \times D_{crise}, \quad ATED_{Vol} = ATE \times D_{vol}$$

In this framework, the coefficient of the attention variable represents its effect during periods outside of crises or high volatility, while the coefficients of the interaction terms indicate how this effect changes during these specific periods. Both the dummies and the interaction terms were included as additional regressors in the ARDL model, maintaining the main dynamic structure with lags of the dependent variable and other regressors. In the robustness tests, the models include 165 observations due to the calculation of rolling volatility with a six-month window. Furthermore, the F-statistics for the cointegration tests were 9.124 in Model 1 and 8.619 in Model 2, exceeding the critical values at the 10%, 5%, and 1% levels, confirming the existence of long-run cointegration. The results are presented in Table V.

Table V – Long- and Short-Term ARDL Estimates for Robustness Tests.

Panel A:	**Long-term estimates**	
Dependent variable: LIQ	Model 1 (Crises and High Volatility Dummies)	Model 2 (Dummies with Attention Interaction Terms)
ATE	1.241**	1.298**
RET	0.032**	0.037**
INF	-1.134**	-1.110**
INTR	-0.687	-0.719
MB	-0.006	-0.010
Panel B:	**Short-term estimates**	
Dependent variable: ΔLIQ	Model 1 (Crises and High Volatility Dummies)	Model 2 (Dummies with Attention Interaction Terms)
$\Delta(LIQ)_{-1}$	0.021	-0.005
$\Delta(LIQ)_{-2}$	-0.123**	-0.132**
Δ(ATE)	8.979***	8.277***
$\Delta(ATE)_{-1}$	2.659**	2.709**
$\Delta(ATE)_{-2}$	3.335**	3.066**
$\Delta(ATE)_{-3}$	1.223	1.156
Δ(INF)	-0.157	-0.125
$\Delta(INF)_{-1}$	0.583**	0.499**
Δ(INTR)	3.315**	3.423***
Δ(MB)	0.057**	0.045
D_{crise}	-0.143	-0.104
D_{vol}	-0.014	-0.023
$ATED_{Crise}$		-3.485**
$ATED_{Vol}$		2.783*
ECM_{-1}	-0.662**	-0.626***
Statistical summary		
R^2	0.751	0.742
R^2 Ajusted	0.749	0.731
$\chi^2_{s/corr}$	0.811(0.787)	0.019(0.984)
χ^2_{het}	1.009(0.452)	1.008(0.455)
χ^2_{norm}	0.794(0.461)	0.266(0.875)
F_{reset}	0.734(0.620)	0.725(0.0625)
CUSUM	Sig. 5%	Sig. 5%
CUSUMSQ	Sig. 5%	Sig. 5%

Note. The variables are liquidity (LIQ), investor attention (ATE), Ibovespa return (RET), inflation (INF), interest rate (INTR), and monetary base (MB). D_{crise} refers to the market crises dummy, D_{vol} refers to the high volatility dummy, $ATED_{Crise}$ is the interaction between attention and crises, and $ATED_{Vol}$ is the interaction between attention and high volatility. Δ denotes the first difference of the respective variable. Diagnostic tests are represented as follows: $\chi^2_{s/corr}$ for the Breusch-Godfrey LM test for serial correlation, χ^2_{het} for the Breusch-Pagan-Godfrey LM test for heteroscedasticity, χ^2_{norm} for the Jarque-Bera test for normality, F_{reset} for the Ramsey RESET test for regression equation misspecification, CUSUM for the cumulative sum of residuals, and CUSUMSQ for the cumulative sum of squared residuals. The error correction term (ECM-1) shows significant coefficients that indicate the speed of liquidity adjustment toward long-term equilibrium after a shock. Significant negative values suggest that liquidity deviations from long-term equilibrium are partially corrected in the subsequent period. All statistics are based on 165 observations. The summary statistics include the test statistics and their p-values in brackets. p-value: 1% = ***, 5% = **, 10% = *.
Source. Prepared by the authors.

The results confirm that investor attention has a positive and statistically significant effect on liquidity in both the long and short run, with the impact persisting across several lags of attention in the short term. The inclusion of crisis and high volatility dummies shows that the direct effects of these regimes are not significant, but the interaction terms indicate that the effect of attention varies according to market conditions: during crises, its impact on liquidity tends to decrease, while in periods of high volatility it is amplified. Following the robustness tests, the results of the main model (Model 5) remain consistent, suggesting that the estimated relationships are robust. The models exhibit good fit, structural stability, and evidence of short- to long-term convergence, further supporting the reliability of the findings.

3.2 Placebo test

As a placebo exercise, we replaced the attention proxy with an unrelated Google Trends search term ("football"). The results indicate that the coefficients of the placebo variable are statistically insignificant, reinforcing that the original findings are not an artifact of using any Google Trends series. The ARDL bounds test yielded an F-statistic of 10.970, exceeding the critical values at the 10%, 5%, and 1% levels, suggesting the presence of long-run cointegration. The estimated ARDL model was (1,0,0,4,1,0). In the long run, the placebo attention variable had a coefficient of -1.392 with $p = 0.208$, while in the short run, there was no significant effect of the (placebo) attention variable on liquidity. In summary, the placebo exercise using an unrelated search term produced statistically null coefficients, further supporting the validity of the attention proxy used in the main model.

4. Final remarks

This study examines the impact of investor attention on Brazilian market liquidity from January 2006 to February 2021, using a broad market index and a multidimensional liquidity measure constructed from three traditional indicators and reduced via PCA. Applying an ARDL framework, the analysis captures both short- and long-term effects of investor attention while controlling macroeconomic variables. The results show that attention significantly influences liquidity across time horizons, remains robust under placebo and other robustness tests, and varies across market conditions such as crises and periods of heightened volatility. These findings contribute to the literature by demonstrating the relevance of investor attention in an emerging market and by highlighting the importance of combining attention measures with macroeconomic controls and multidimensional liquidity indicators. They also offer practical implications for investors, policymakers, and regulators concerned with informational uncertainty and liquidity risk.

The study has limitations. It does not assess possible asymmetries between positive and negative attention, which future research could explore using nonlinear ARDL (NARDL) models. Extending the dataset with alternative attention and liquidity measures, longer time spans, or higher-frequency data would also strengthen the generalizability of the results. Incorporating commonly used liquidity metrics such as Amihud illiquidity, bid-ask spread, and turnover could improve comparability with international studies and allow a more detailed examination of liquidity behavior under different market regimes. Overall, the findings confirm that investor attention is a significant determinant of liquidity in the Brazilian market, with effects that remain consistent across specifications, market conditions, and methodological approaches, providing a solid basis for future research on investor behavior and market efficiency.

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