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The Effect of Local Participation on Market Pricing and Liquidity: Evidence from an Emerging Market

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Abstract This study aimed to investigate the relationship between local stock market participation and market return-liquidity from the perspective of an emerging market—Turkey. In this context, the main research question is how investor attendance at different wealth levels influences market returns and liquidity. It is an established assumption that as wealth increases, the probability of being a rational investor also increases. We, because of multicollinearity in our models, employed statistical shrinkage methods-Ridge Regression, Lasso Regression, and Elastic Net Regression. While groups with low-level wealth were found to be the most important determinants for market liquidity, they were not predictors of market return. However, wealthier investors had positive coefficients in stock return models. Robustness tests confirmed the previous findings. These findings imply that those who consider investing in capital markets should have a long-run investment horizon; otherwise, they cannot sustain their presence in the market, as demonstrated in this paper. This is the first study to analyze the impact of retail investors on both stock market return and liquidity using nationwide data.

Keywords Personal Finance, Capital Markets, Stock Market Participation, Noise Trader, Multicollinearity, Statistical Shrinkage Methods

1. Introduction

Fama [1] argues against the presence of irrational investors in efficient markets. Behavioral finance researchers, however, have provided a myriad of empirical evidence demonstrating an array of anomalies in the stock markets (see a detailed literature review by Goodell et al. [2]). Two long-known anomalies in the financial literature are: the noise trader and the equity premium puzzle. On the one hand, Black [3] describes noise traders as investors who trade without considering fundamentals. He alleges that while noise traders are necessary for market liquidity, they also make it difficult to estimate the price of securities. On the other hand, Mehra and Prescott [4] report that the long-term returns of stocks in the U.S stock market are higher than the yields of the risk-free rate (treasury bill). This finding raises the question of why rational traders are reluctant to participate in the stock markets, a discrepancy known as the equity premium puzzle.

Researchers have attempted to unravel this puzzle by using various parameters, such as 'corporate scandals' Giannetti and Wang [5], 'windfall gains' Briggs et al. [6], 'social interaction' Hong, Kubık, and Stein [7], 'internet access' Lopez, Ares, and Vivel-Bua [8] and Liang and Guo [9], 'IQ' Grinblatt, Keloharju, and Linnainmaa [10] and 'gender role asymmetry' Barasinska and Schäfer [11]; Almenberga and Dreber [12]; and Ke [13]. Nevertheless, researchers have reported a noticeable increase in stock market participation rates among households in developing countries over the last decade [14,15]. These studies can be grouped into two main categories: the former focuses on the determinants of households' stock market participation decisions (e.g., internet access, gender), while the latter investigates if retail investors exhibit behavioral biases (e.g., overconfidence, familiarity bias). Interestingly, the effect of retail investors' stock market participation decisions on market pricing and liquidity has attracted little interest from researchers [16]. With this study, we aimed to fill this gap in the literature.

Moreover, there is a growing body of evidence regarding the effect of demographic variables (such as wealth, age, gender, marital status, and so on) on investors' trading behaviors [17-24]. The common feature of these studies is that they analyze the relationship between investor behaviors and demographic variables using survey data from a certain subgroup of retail investors. Also, while some studies address the impact of demographic variables on investors' risk perception [17,18], others analyze the way investor demography affects behavioral biases [19,20].

In this study, we aimed to investigate the effects of stock market participation at varying wealth levels on market liquidity and returns. We presumed that the prospect of being an irrational investor declines with wealth: low-wealth level investor groups are irrational investors, high-wealth level groups are informed traders, and passive traders fall in between them [16]. Simply put, noise traders, albeit known as liquidity traders, cannot consistently beat the markets, as their success is often due to luck and taking more risks. As long as taking risks is rewarded by the market, they will earn money [25]. Although some new evidence from Bogousslavsky and Muravyey [26] shows that retail traders may not just be uninformed traders who lose money, they still might not engage in sustainable investment planning. For this study, we employed two different dependent variables: the monthly return of the BIST-100 Return Index (BIST-R) and the BIST-100 trading volume (Ln(TV)). Following Kelly [16] and Adrianto and Hamidi [15], we used a demographic variable (wealth) as a proxy to distinguish between noise traders and sophisticated investors. Thus, our independent variables were the number of retail investors categorized into seven groups based on their stock investment amounts in BIST. Our research period covered ten years, from January 2013 to October 2023. In an effort to obtain the best estimation model, our sample was divided into two subsets for each dependent variable: training set (70%) and test set (30%). We, on account of multicollinearity in our regression models, applied three statistical shrinkage methods: Ridge Regression, Lasso Regression, and Elastic Net Regression. We also used one of the Robust Covariance Matrix Estimator techniques [27]. Additionally, one of our dependent variables, BIST-R, is a financial time series, which means it may have outliers. Thus, we employed Trimmed Least Squares Models (TLS) [28,29] to address the outlier issues in our dependent variable. Consequently, the current study contributes to the existing literature in a wide range of ways:

To the best of our knowledge, studies analyzing the results of market participation by retail investors focus on the influence of either market return [16] or market liquidity [30,31]. This study represents the first attempt to investigate the effects of retail investors on both market return and liquidity using nationwide data.

As mentioned above, papers analyzing how demographic variables affect investors' behaviors typically use survey data limited to specific sub-samples of investor groups. We criticize this method for two reasons. Firstly, the findings of these studies may not be easily generalized. Gümüş and Dayıoğlu [18], for example, analyzed how the demographic features of a group of 100 retail investors influenced their risk preferences using data from a brokerage house. However, during this period, the number of retail investors in BIST was over one million. Secondly, the survey method has various disadvantages. For instance, survey participants, because of the way the information is conveyed, may not fully understand the questions, leading to potentially inaccurate answers. Taking Weber and Milliman [32] as an example, they suggest that the presentation of information can influence individuals' risk perception during decision-making in risky situations. Also, Jianakoplos and Bernasek [33] reported a contradiction between male participants' responses regarding their risk tolerance and their actual investments. Hence, following the approach of Tekçe and Yılmaz [34], we utilized the total number of retail investors across the country.

Most studies addressing how limited stock market participation affects market return and volatility were conducted in developed countries [35,36]. Developing countries, however, differ from developed ones in many aspects. Firstly, capital markets in developing countries often have a weak legal and institutional framework. Secondly, retail investors in these countries are more likely to be less educated; in other words, their financial literacy level is relatively low, leading them to trade based on rumours [19]. Therefore, it is pivotal to understand the effect of retail investors on capital markets in emerging markets. In this way, this study contributes to behavioral finance literature by analyzing retail investors' impact on capital markets in an emerging market, Turkey.

Retail investors' behaviors vary from those of institutional investors. They usually manage their own investments and have limited funds to diversify their portfolios [20]. Over the last three years, the number of retail investors in Turkey has skyrocketed. Figure 1 shows the increase in the number of local retail investors.

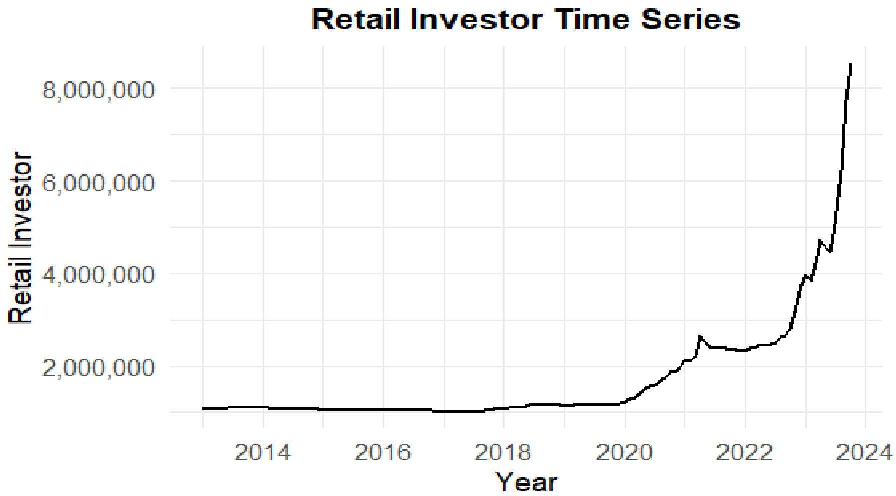

Figure 1. Local Retail Investor Statistics (January 2013-October 2023)

Local investors constitute 99.4% of the total investors in BIST. Among local investors, retail investors make up 99.7%, holding 55% of the total local portfolio value. Furthermore, local retail investors' trading accounts for 78% of the total transaction volume in BIST [37]. These data motivated us to investigate how local retail investors impact market return and liquidity.

The rest of the study is structured as follows: Section 2 discusses relevant literature, Section 3 presents the econometric approaches, Section 4 defines the sample and variables of the study, Section 5 reports the findings, Section 6 provides additional test results, Section 7 concludes the study, and Section 8 explains the limitations of the paper and suggests areas for future research.

2. Literature Review

As far as we know, there are few studies concerning the results of market participation. In his groundbreaking study, Kelly [16] uses wealth as a proxy for the likelihood of being a noise trader and categorizes American retail investors into three groups: high-wealth groups as smart money, low-wealth groups as noise traders, and passive investors in between. He employed OLS regression to estimate p-values for one-year return estimations and a QS kernel for three-year estimations, using the MacKinnon-White jackknife technique. To address the issue of extreme values in financial time series, the least median of square method was applied. While the stock market participation of retail investors with low wealth levels (noise traders) is negatively correlated with stock returns, the participation of high wealth-level (smart money) investors is positively associated with stock returns. Also, passive investors have no significant effect on predicting stock returns.

Amihud, Mendelson, and Uno [30] analyze the impact of changes in the Minimum Trade Unit (MTU) in the Tokyo Stock Exchange between 1991 and 1996 by employing OLS regression models. They find that companies reducing their MTU tend to have a broader shareholder base and increased liquidity.

According to Mattana and Panetti [38], the economic slowdown and fixed entry costs prevent retail investors from participating in the stock market and make deposit accounts more appealing for households, increasing liquid assets in their portfolios, and vice versa. They establish a theoretical model- a two-period overlapping-generation growth model in their study.

Ahn et al. [36] investigate the relationship between stock market efficiency and retail investor participation using the data on the reduction in MTUs (minimum trading units), employing OLS regression and a Probit model. They report that an increase in the number of retail investors in the Tokyo Stock Exchange raises liquidity, yet the prices of stocks are prone to be less volatile. They put forward that noise trading leads informed traders to trade more aggressively, making the prices of assets more efficient.

Zhang [35] analyzes the effect of local retail participation on stock liquidity using county-level racial composition as a proxy, employing OLS models. He proposes shares in counties with a higher percentage of the white population are more liquid due to retail investors' tendency to exhibit familiarity bias.

Chia, Lim, and Goh [31] provide evidence of a nonlinear relationship between the number of shareholders and liquidity. As the number of retail investors increases, stock liquidity rises. However, the negative impact of this trend occurs when the number of retail investors exceeds a threshold level. They allege that the predicted threshold level is much higher than the number of retail investors in the companies listed on the Malaysian Stock Exchange.

Xiong, Wang, and Shen [39] investigate the relationship between equity market participation and the herding behavior of retail investors in the Chinese stock market using the Yu'e Bao market participation willingness index.

They use nonlinear regression equations based on the cross-sectional absolute deviation of returns (CSAD) and report a positive correlation between the market participation willingness of retail investors and herding behavior becomes more pronounced when the index is at a high level.

3. Econometric Models

In econometric analyses, multiple linear regression is usually used to estimate a dependent variable with more than one independent variable, whose mathematical notation is as follows:

$$y = \beta_0 + \beta_1 X_1 + \ldots + \beta_n X_n + \varepsilon \qquad (1)$$

where,

y is the dependent variable

β_0 is the intercept

β_1 is the independent varaible

ε is the error term

One of the basic assumptions of the multiple regression model is the independence of explanatory variables, referred to as multicollinearity. If there is a high correlation among independent variables in a regression model, this can result in a high-variance, low-bias model. To detect multicollinearity, the following methods can be used [40]:

- Examining the correlation matrix between explanatory variables
- Examination of Variance Inflation Factors (VIF) of explanatory variables

One solution to overcome multicollinearity is to employ statistical shrinkage methods such as Ridge Regression, Lasso Regression, and Elastic Net Regression.

3.1. Ridge Regression

Like other techniques, Ridge regression, known as L2 regularization, uses a penalty term added to each independent variable. In this way, the coefficient of an explanatory variable that has no significant impact on the dependent variable approaches zero.

$$\text{MSE} + \lambda \sum_{j=1}^{p} \beta j2 \qquad (2)$$

where MSE represents mean square error, and λ is a penalty term that allows controlling the coefficients in the regression model. As λ increases, the coefficients of the model get close to zero, though not equal to zero. Unlike OLS regression, the Ridge regression approach estimates an array of coefficients depending on the λ parameter [41]. Therefore, it is essential to define the best λ to obtain a model with the least MSE. In practice, the cross-validation method is usually used to determine the best λ.

3.2. Lasso (Least Absolute Shrinkage and Selection Operator) Regression

Lasso regression, known as L1 regularization, is similar to Ridge regression, but Lasso regression has some differences from Ridge regression. In contrast to Ridge regression, the coefficients of the variables that have no significant effect on the model go to zero and are omitted from Lasso Regression. The most defining feature of this model is a variable selection, which makes it easy to interpret the model outcomes [42].

$$\text{MSE} + \lambda \sum_{j=1}^{p} |\beta j| \qquad (3)$$

3.3. Elastic Net Regression

Although Lasso regression provides simpler models to comment on, this method has some restrictions [42]:

- When the number of variables outnumbers the number of observations (p > n), the Lasso method selects most n variables, making it a limiting feature for the variable selection method.
- In cases where pairwise correlations are high among a panel of variables, the Lasso method is prone to randomly selecting only one variable from this group.

On the other hand, Elastic Net Regression is a combined version of L1 and L2 regularization, which means this method considers both variable selection and group effects [43].

$$\text{Argmin}|y - X_\beta|^2,\ (1\text{-a})|\beta_1| + a|\beta|^2 \leq t \qquad (4)$$

where (1-a) $|\beta_1|$ + a$|\beta|^2$ is the penalty term of Elastic Net Regression. As Elastic Net Regression is a combination of Ridge and Lasso, it incorporates both the Ridge penalty term and the Lasso penalty term.

4. Methodology

4.1. Sample and Variables

In this study, we examined the influence of local retail equity market participation at varying wealth levels on market return and liquidity using statistical shrinkage methods. The research period spanned ten years, from January 2013 to October 2023. The sample was divided into two subsets for each model: a training set (70%) and a test set (30%) as it yielded the best prediction results, with the lowest estimation error and the highest R^2, compared to other alternatives such as %80-20 and %60-40. Monthly data was employed for the analysis. In this section, we presented our dependent and independent variables.

4.1.1. Dependent Variables

Our first dependent variable was market return (BIST-R). We obtained the monthly closing prices of the BIST-100 Return Index from the Central Bank of the Republic of Turkey [1] (CBT) and calculated the logarithmic return

[1] https://evds2.tcmb.gov.tr/index.php?/evds/serieMarket (Accessed: 13.12.2023)

values using the following formula:

$$rt= \ln(\frac{pt}{pt-1}) \tag{5}$$

where rt is the monthly return of the stock market, p_t is the closing price of BIST-100 Return Index in month t and, p_{t-1} is the closing price of BIST-100 Return Index in month t-1.

The second dependent variable was the trading volume of the BIST-100 Index. We acquired monthly trading volume data from the Ideal Data Financial Technologies Inc database [2]. Trading volume was calculated by multiplying the transaction sum of a stock by the price of the stock. In addition, considering the relatively high inflation rate in Turkey during the research period, the trading volume data were deflated using the following formula:

$$\text{real value}_t=(\frac{\text{Current Price Valuet}}{\text{Consumer Price Indext}})*100 \tag{6}$$

4.1.2. Independent Variables

As we used wealth as a proxy for the probability of being a noise trader, the independent variables were the number of retail investors based on their stock investment amounts in BIST. According to CRA data, local retail investor statistics were categorized into seven groups[3]. Table 1 displays each group, their explanations, and our expectations for them to predict market returns and liquidity. For example, each investor in Group 1 holds up to 1000 Turkish Lira in stock investments. We define them as noise traders, meaning they are not positive predictors of market returns, but they do contribute to market liquidity. We incorporated the change rates of these variables compared to the previous month in the model.

4.1.3. Control Variables

After the Covid-19 pandemic, Turkey, like other countries, implemented an expansionary fiscal policy, which involved lowering interest rates and increasing the money supply, leading to a rise in inflation rates in subsequent periods[4]. This extraordinary period prompted us to incorporate some macroeconomic variables into our study. Thus, two macroeconomic variables were also added to the models: Consumer Price Index (CPI), Money Supply (M2).

We got CPI data from Turkish Statistical Institute[5], and used the monthly rate of change. In addition, we obtained M2 data from Central Bank of Turkey[6]. We calculated the rate of change compared to the previous month.

[2] We obtained the data from the company by requesting it via email at estore@idealdata.com.tr. The data on transaction volume will be provided by the corresponding author upon request.
[3] In Turkey, CRA provides investor statistics for scientific research via this e-mail: vaptalep@mkk.com.tr. The data on investor statistics will be provided by the corresponding author upon request.
[4] https://www.sbb.gov.tr/wpcontent/uploads/2023/06/GenelFaaliyetRaporu-2020.pdf (Accessed: 13.12.2023)
[5] https://data.tuik.gov.tr/Kategori/GetKategori?p=enflasyon-ve-fiyat-106&dil=1 (Accessed: 13.12.2023)
[6] https://evds2.tcmb.gov.tr/index.php?/evds/serieMarket (Accessed: 13.12.2023)

All in all, we established two separate models for two different dependent variables:

Market Return= f (Investor Groups; Contorls; error)

Market Liquidity= f (Investor Groups; Contorls; error)

Table 1. Investor Groups and Their Explanations

Investor Group	Portfolio Value (Turkish Lira)	Definition	Return	Liquidity
Group 1	Holding upto 1000 TL	Noise	Negative	Positive
Group 2	Holding from 1001 to 10000 TL	Noise	Negative	Positive
Group 3	Holding from 10001 to 50000 TL	Passive	No effect	No effect
Group 4	Holding from 50001 to 100000 TL	Passive	No effect	No effect
Group 5	Holding from 100001 to 500000 TL	Informed	Positive	Positive
Group 6	Holding from 500001 to 1000000 TL	Informed	Positive	Positive
Group 7	Holding 1000001 and above TL	Informed	Positive	Positive

5. Empirical Results

5.1. Initial Analyses

In this section, we presented our findings. We used R Studio to conduct statistical tests. Table 2 illustrates the percentage of investor groups within the total number of local investors during the research period. Groups 6 and 7, holding the highest portfolio shares, had the lowest percentages in the total investor numbers, 1.03% and 0.91%, respectively. The loftiest portion belonged to Group 2. While Group 3 had the second-largest segment, Groups 4 and 5 had similar percentages.

Table 2. Average Distribution of Investor Groups in BIST (January 2013-October 2023)

Group 1	Group 2	Group 3	Group 4	Group 5	Group 6	Group 7
8.49 %	60.39 %	16.85 %	5.65 %	6.68 %	1.03 %	0.91 %

Table 3 presents the descriptive statistics of our variables. While the mean return of the stock market was 2%, the standard deviation (risk) of this investment instrument was moderately high at 6.7%, which may provide researchers with insights into the equity premium puzzle in Turkey. The investor statistics for Group 7 and Group 6 exhibited the highest volatility, with the highest standard deviation. Following the implementation of expansionary fiscal policies in Turkey during the COVID-19 pandemic, inflation rates commenced to rise. The highest inflation rates were recorded as 13.58% in December 2021 and 11.10% in January 2022, respectively.

Table 3. Descriptive Statistics

	N	Mean	Median	Max	Min	Std.Dev
BIST-R	130	2.042	1.550	21.890	-19.190	6.7914
Ln(TV)	130	14.73	14.53	16.55	13.46	0.7089
Group 1	130	-0.0076	-0.0051	0.1158	-0.1694	0.0431
Group 2	130	0.0170	-0.0010	0.4081	-0.1113	0.0707
Group 3	130	0.0197	0.0077	0.3367	-0.0479	0.0477
Group 4	130	0.0232	0.0176	0.2426	-0.1440	0.0521
Group 5	130	0.0280	0.0189	0.3316	-0.1222	0.0591
Group 6	130	0.0334	0.0256	0.3694	-0.1402	0.0757
Group 7	130	0.0355	0.0263	0.3450	-0.1601	0.0844
CCI	130	1.6542	1.0450	13.58	-1.44	2.1856
M2	130	2.2405	1.9835	15.1469	-4.7063	2.7398

Note: BIST-R represents the monthly return of BIST-100 Return Index, Ln(TV) represents the trading volume of BIST-100 Index, CCI represents monthly inflation rates, and M2 represents monthly Money supply.

Our research period covered ten years, from January 2013 to October 2023. In time series analyses, the data used must be stationary. The Augmented Dickey Fuller Test is often employed to check the stationarity assumption. Before conducting regression tests, we ran the ADF test using the 'urca' package with the Akaike Information Criterion (AIC) and 12 lags. All our variables were stationary at the 1% significance level (see Appendix A). One of the basic assumptions of regression analysis is the independence of explanatory variables. To test the independence assumption of the variables, we calculated correlation coefficients for independent variables using the 'Hmisc' and package. Table 4 displays a significant and high correlation among investor groups. To mitigate the issue of multicollinearity in our models, we employed statistical shrinkage methods, including Ridge Regression, Lasso Regression, and Elastic Net Regression.[7]

5.2. Results of Return Models

In this section, we presented the findings of the regression analyses. We conducted Ridge Regression, Lasso Regression, and Elastic Net Regression for each dependent variable (BIST-R and Ln(TV)) using the 'caret' and 'glmnet' packages in R Studio. We initially acquainted the results of the BIST-R model. Table 5 displays the results of all three models. Although both Lasso and Elastic Net had the lowest Mean Squared Error (MSE), the R^2 of Elastic Net was higher than the other two models, indicating that the Elastic Net model was the best predictor of market returns. As wealth levels rose, the coefficients of the groups exhibited a corresponding increase. While Group 1 was a negative predictor for market return, Groups 5, 6, and 7 had positive coefficients in all models. Notably, the coefficients of Group 6 and Group 7, representing the smallest share in total investor numbers (1.03% and 0.91%, respectively), were the highest. However, the participation of Group 2, the largest segment among local investors (60.39%), had no important effect on predicting market returns. Lastly, Group 2, Group 3, and Group 4 had positive, and negative coefficients, respectively, but they were quite low, meaning their coefficients had no economic importance. In contrast, Group 1, Group 6, and Group 7 had relatively high coefficients, leading us to infer that their coefficients had economic importance. Control variables had quite low coefficients.

These results were consistent with findings from previous studies. Kelly [16] reports that low-wealth level investors often have limited funds and trade based on rumors rather than fundamentals. Furthermore, intermediate groups examined in his study have no significant power in predicting stock prices. Al-Mukit [20] investigates the relationship between demographic variables, such as financial literacy, wealth, risk profile, and trading behaviors among 100 retail investors on the Indonesia Stock Exchange. They measure investors' wealth based on their stock investment amounts, noting that traders with higher portfolio values are more inclined to choose blue-chip stocks. In the cross-sectional study using nationwide retail investor data from CRA, Tekçe, Yılmaz, and Bildik [44] analyze how demographic variables relate to behavioral biases. They report that wealthier investors tend to choose stocks whose prices have recently increased.

5.3. Results of Trading Volume Models

In this section, we presented the results of regression models whose dependent variable was the trading volume of the BIST-100 Index. Table 6 displays the outcomes of these models. Elastic Net Regression emerged as the most accurate predictor of the trading volume of the BIST-100 Index, exhibiting the highest R^2 and the lowest MSE.

[7] In fact, we tried to combine the independent variables with high correlation (Group 1, Group 4, Group 5, Group 6, and Group 7), but we could not solve the multicollinearity problem. We, therefore, continued the analysis by adhering to the format provided by CRA.

Group 1 and Group 3 had the two highest positive coefficients in all models. A plausible explanation for this result is that these investors may have exhibited an overconfidence bias, leading them to trade aggressively. After all, there could be a potential decrease in their wealth level [34]. As mentioned earlier, Groups 1 and 3 were not positive predictors of market return, suggesting that they might have traded without considering fundamentals. Another explanation is associated with gambling behavior, often observed in developing countries. Retail investors residing in developing countries are more likely to exhibit gambling behavior compared to those in developed ones, mainly due to their relatively low income levels. Thereof, so as to get immediate gain, investors may be on the hunt for high-risk (i.e, expected return) investments without proper risk evaluation [19]. The data supporting these findings came from the CRA; the lock-up period for stocks among local retail investors was 18 days in 2020.

The equity market participation of Group 4 was not an estimator for market liquidity. Additionally, both Group 5 and Group 6 exhibited relatively low coefficients vis-a-vis Group 2 and Group 3 across all models. This outcome may be linked to these investors adopting a passive strategy. Intermediate groups could tend to favor long-term investments, diversifying their portfolios with other securities [20]. Another explanation is that these groups may have displayed a status quo bias, meaning they did not frequently change their portfolio compositions, unlike investors with low-wealth levels [44]. Furthermore, considering the positive and high coefficients of these groups (Group 6 and Group 7) in return models, it is likely that their investments were managed by intermediary institutions. Unlike the return models, one of the control variables—money supply—had relatively high and positive coefficients across all models. This finding suggests that retail investors invested in the stock market as the money supply expanded.

All in all, the findings obtained from the analyses carried out so far met our expectations. Although the coefficients of liquidity traders do not have economic importance in return models, their presence appears to be necessary for the market to remain liquid.

Table 4. Correlation Matrix

	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6	Group 7
Group 1	1						
Group 2	-0.214**	1					
Group 3	-0.403***	0.473***	1				
Group 4	-0.571***	0.199**	0.684***	1			
Group 5	-0.777***	0.067	0.584***	0.828***	1		
Group 6	-0.804***	0.003	0.437***	0.689***	0.917***	1	
Group 7	-0.850***	-0.008	0.378***	0.637***	0.894***	0.918***	1

Note: ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 5. Return Model Results

Ridge		Lasso		Elastic Net	
Variables	Coefficient	Variables	Coefficient	Variables	Coefficient
Group 1	-0.5629	Group 1	-0.5700	Group 1	-0.5512
Group 2	-0.0334	Group 5	0.0641	Group 5	0.1432
Group 3	0.0351	Group 6	0.4409	Group 6	0.3676
Group 4	-0.0446	Group 7	0.1526	Group 7	0.1748
Group 5	0.2425				
Group 6	0.3076				
Group 7	0.1845				
CCI	-0.0004				
M2	0.0380				
Constant	0.0019	Constant	0.0025	Constant	0.0021
N	130	N	130	N	130
R^2	0.7496	R^2	0.7465	R^2	0.7543
MSE	0.0009	MSE	00009	MSE	0.0009
Lamda	0.0073	Lamda	0.0028	Lamda	0.0047
				Alpha	0.5

Note: CCI represents monthly inflation rates, and M2 represents monthly money supply.

Table 6. Trading Volume Model Results

Ridge		Lasso		Elastic Net	
Variables	Coefficient	Variables	Coefficient	Variables	Coefficient
Group 1	8.3761	Group 1	10.2202	Group 1	9.4977
Group 2	3.4959	Group 2	3.8139	Group 2	3.6829
Group 3	4.5500	Group 3	4.3730	Group 3	4.3991
Group 4	-0.4987	Group 6	2.7939	Group 6	2.8649
Group 5	0.5623	Group 7	5.5226	Group 7	5.0964
Group 6	3.0898	CCI	0.0692	CCI	0.0722
Group 7	4.1822	M2	2.8124	M2	3.0426
CCI	0.0761				
M2	3.4567				
Constant	14.4502	Constant	14.4298	Constant	14.4382
N	130	N	130	N	130
R^2	0.0261	R^2	0.0281	R^2	0.0350
MSE	0.2934	MSE	0.2928	MSE	0.2908
Lamda	0.0438	Lamda	0.0127	Lamda	0.0193
				Alpha	0.6

Note: CCI represents monthly inflation rates, and M2 represents monthly money supply.

6. Additional Tests

In this section, we conducted several additional tests to corroborate our previous findings for two reasons. First, as shown in Table 4, there were high and significant correlations between our independent variables. This concern needs to be alleviated to estimate the coefficients in the OLS regression without bias. Alongside statistical narrowing techniques, we also used the heteroscedasticity and autocorrelation consistent covariance matrix proposed by [27]. This approach is known to provide unbiased results, especially in studies with small samples [45]. Given that we divided the sample of 130 observations into 70% and 30%, we found it more logical to use the [27] procedure to demonstrate the robustness of our previous findings. Analyses were performed in R Studio using the 'sandwich' and 'lmtest' packages. The results for both dependent variables are shown in Table 7. In the return model, Group 1 has a negative and significant coefficient, Group 6 and Group 7 have positive and significant coefficients, Group 3 has a statistically insignificant coefficient, and Group 4 has an economically insignificant coefficient. In the liquidity model, Group 1 has the highest positive and significant coefficient, while Group 4 does not have a significant coefficient. In short, the results largely confirm the findings shown in the previous section.

Second, financial time series, especially volatile investment tools such as stocks, tend to have outliers. To address this concern in our study, we used the Trimmed Least Squares Estimation (TLS) technique [29], which is sensitive to extreme values. Although the Least Median of Squares technique is also used for the same purpose, it is reported that TLS gives better results, especially when outliers constitute less than 50% of the entire dataset [28]. This analysis was performed using the 'MASS' package in R Studio. We initially detected outliers in the BIST-R variable. To examine this, we created a box plot using the 'ggplot2' package. Figure 2 shows that our return variable has outliers.

Table 7. OLS Regressions with Newey-West Predictors

BIST-R		LnTv	
Variables	Coefficient	Variables	Coefficient
Group1	-0.7601***	Group1	11.129***
Group2	-0.0414	Group2	4.3655***
Group3	0.0202	Group3	5.5985***
Group4	-0.0784*	Group4	-0.0181
Group5	0.1515	Group5	-6.296**
Group6	0.2034*	Group6	3.3759
Group7	0.2390	Group7	8.6468***
CCI	0.0005	CCI	0.0549
M2	0.0376	M2	0.8871
Constant	0.0062***	Constant	14.3893***
N	130	N	130
Adjusted R^2	0.8895	Adjusted R^2	0.5399

Note: ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively; CCI represents monthly inflation rates, and M2 represents monthly money supply.

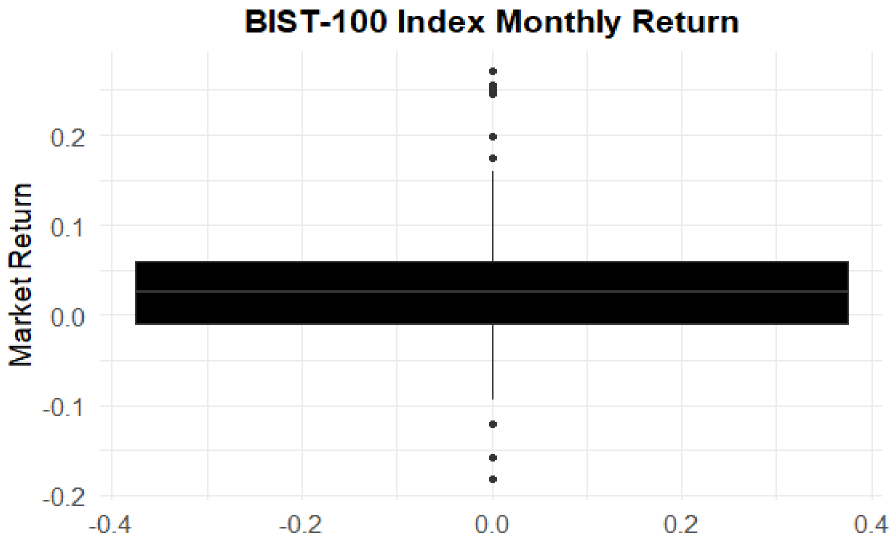

Figure 2. Box-Plot of BIST-100 Index Monthly Return

Table 8 displays the coefficient results of the TLS model. However, caution should be exercised when examining these coefficient values. Since the coefficients do not have standard errors and p-values, comparisons can be made based on the sizes of the OLS regression coefficients given in the previous section. In other words, a comparison can be made based on the economic importance of the coefficients. When looking at the coefficients in general, we saw that outliers in the return variable were not a serious source of concern.

Table 8. Trimmed Least Squares and OLS Regression Results

TLS Regression		OLS Regression	
Variables	Coefficient	Variables	Coefficient
Group1	-0.9652	Group1	-0.7601
Group2	-0.0256	Group2	-0.0414
Group3	0.0071	Group3	0.0202
Group4	-0.2514	Group4	-0.0784
Group5	0.4367	Group5	0.1515
Group6	0.057	Group6	0.2034
Group7	0.0982	Group7	0.2390
CCI	0.0038	CCI	0.0005
M2	0.0288	M2	0.0376
Constant	0.0125	Constant	0.0062

7. Conclusions and Discussion

It was meant to analyze the relationship between local equity market participation and market return-liquidity using nationwide data. Following Kelly [16], we used wealth (stock investment) to differentiate among investor groups. Noise traders are essential for market liquidity but make it difficult to estimate security prices because they do not trade based on fundamentals. Our findings substantially confirmed this approach. Although groups with low-level wealth (Noise Trader) contributed the most to market liquidity, they were not predictors for market return, implying that they traded on BIST without considering fundamentals. However, while wealthier investors' participation (Informed Trader) was a positive predictor of monthly market return, we did not observe a similar finding for participants with low wealth levels. Our findings have defining implications for retail investors:

They should not perceive the stock market as a 'gaming house.' Creating a sustainable investment strategy by trading, on average, every 18 days is not sustainable. Wealthier investors, in particular, may be able to compensate for their losses, yet investors with lower wealth levels should exercise greater caution and seek assistance from professional institutions when making investment decisions. The statistics that corroborate this fact came from CRA. Figure 3 shows the number of retail investors in Group 1 and Group 7. While the number of investor groups with low wealth (Group 1) has steadily decreased, the number of investor groups with high wealth (Group 7) has increased.

M2–one of control variables– was a positive predictor of market liquidity. Decreasing interest rates and expanding the money supply may have increased the stock market's appeal to investors benefiting from monetary expansion, such as improved access to banking credit during the COVID-19 pandemic. This inference is supported by the rate of change in investor groups' stock market investment amounts. We measured the difference in stock investment amounts (TL) of investor groups between the beginning and the end of the research period. Our findings show that the largest percentage increase occurred in Group 6 (541%) and Group 7 (499%), while the smallest increase was observed in Group 3 (45%) and Group 1 (-95%).

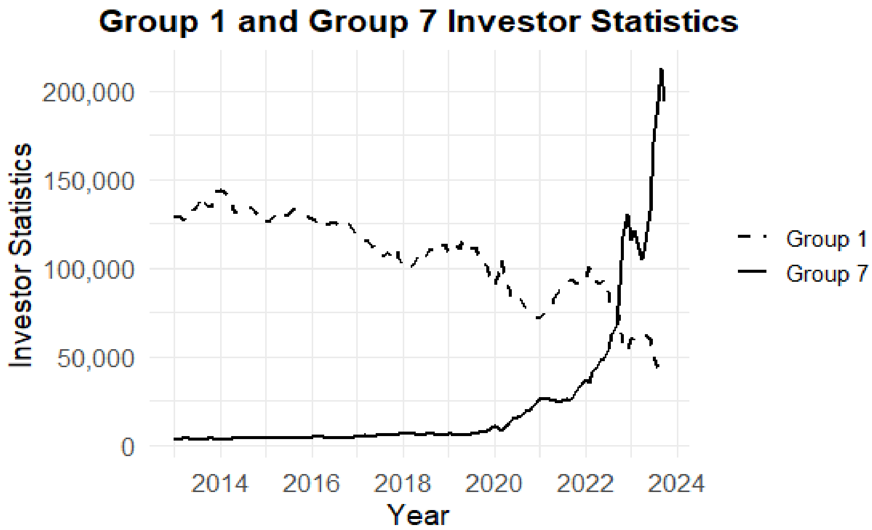

Figure 3. Investor Statistics of Group 1 and Group 7 (January 2013-October 2023)

Appendix

Appendix A. Unit Root Test Results

	ADF		ADF		ADF		ADF
BIST-R	t-Statistics	Ln(TV)	t-Statistics	Group1	t-Statistics	CCI	t-Statistics
	-6.6534***		-4.3095***		-3.6873***		-4.5229***
1%	-3.99	1%	-3.99	1%	-3.99	1%	-3.99
5%	-3.43	5%	-3.43	5%	-3.43	5%	-3.43
10%	-3.13	10%	-3.13	10%	-3.13	10%	-3.13
	ADF		ADF		ADF		ADF
Group2	t-Statistics	Group3	t-Statistics	Group4	t-Statistics	M2	t-Statistics
	-8.109***		-5.6119***		-6.0367***		-7.5181***
1%	-3.99	1%	-3.99	1%	-3.99	1%	-3.99
5%	-3.43	5%	-3.43	5%	-3.43	5%	-3.43
10%	-3.13	10%	-3.13	10%	-3.13	10%	-3.13
	ADF		ADF		ADF		
Group5	t-Statistics	Group6	t-Statistics	Group7	t-Statistics		
	-6.5049***		-6.9751***		-6.7164***		
1%	-3.99	1%	-3.99	1%	-3.99		
5%	-3.43	5%	-3.43	5%	-3.43		
10%	-3.13	10%	-3.13	10%	-3.13		

Note: ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively; CCI represents monthly inflation rates, and M2 represents monthly money supply.

8. Limitations and Implications for Future Research

Although the results of this study are supported by different statistical techniques, it has some limitations. The first limitation relates to the dataset. When we requested data from CRA, we asked for investor statistics starting from December 2005, but CRA provided the dataset starting from January 2013. Notwithstanding our additional analyses mitigating the small sample concern, future studies can conduct analyses with higher frequency data (e.g., daily or weekly transaction volume). Second, in this study, we assumed that the investor groups were internally homogeneous. However, there may be investors engaging in liquidity trading within Group 7, which we define as informed investors. For example, some speculators, such as George Soros, argue that joining noise traders is a way to beat them [46]:

> *"The key to success, says Soros, was not to counter the irrational wave of enthusiasm about conglomerates, but rather to ride this wave for a while and sell out much later. Rational buying by speculators of already overvalued conglomerate stocks brought further buying by the noise traders, and enabled the speculators to make more money selling out at the top."*

Therefore, future studies could examine individual accounts within investor groups in more detail. Third, our sample includes only Turkish investors. In future studies, conducting comparative analyses on the impact of demographic factors on market return and liquidity in countries where individualism and collectivism are observed, as suggested by Fan and Xiao [47] and Statman [48], would be interesting.

Declaration of Conflict of Interest

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

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