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Research Article / *Araştırma Makalesi*

DO HIGH-FREQUENCY TRADING AFFECT BUBBLE FORMATION IN STOCK MARKETS? EVIDENCE FROM EMERGING STOCK MARKET

Mehmet Sinan ÇELİK[1]

ABSTRACT

This study examines the factors affecting bubble formation in the Turkish stock market Borsa Istanbul (BIST), an important emerging market where high-frequency trading (HFT) is a relatively new phenomenon. HFT refers to trades executed using fast algorithms and has become an essential dynamic of financial markets today. The study uses intraday and daily stock price data between 11 March 2020 and 31 December 2020. The data are obtained from Borsa Istanbul and HFT activities are identified with 'intraday order' data. The existence of speculative bubbles is tested using Supremum Augmented Dickey-Fuller (SADF) and Generalised Sup Augmented Dickey-Fuller (GSADF) models. The study finds that HFT transactions play an important role in bubble formation. With their high trading volumes and fast trading capabilities, HFT trades can create excessive volatility and manipulation in the market. This may increase the risk of bubble formation. The study emphasises the importance of regulation and supervision in mitigating HFT effects in financial markets. Regulations aimed at increasing transparency in the market can help investors make more informed decisions.

Keywords: *Algorithmic Trading; High-Frequency Trading Volatility; Liquidity; Speculative Bubbles*

JEL Classification Codes: *G12, G17, G19*

YÜKSEK FREKANSLI İŞLEMLER HİSSE SENEDİ PİYASALARINDA BALON OLUŞUMUNU ETKİLER Mİ? GELİŞMEKTE OLAN HİSSE SENEDİ PİYASASINDAN KANITLAR

ÖZET

Bu çalışma, yüksek frekanslı işlemlerin (HFT) nispeten yeni bir olgu olduğu önemli bir gelişmekte olan piyasa niteliğindeki Türk hisse senedi piyasası Borsa İstanbul (BIST)'da balon oluşumunu etkileyen faktörleri incelemektedir. HFT, hızlı algoritmalar kullanılarak gerçekleştirilen işlemleri ifade eder ve günümüzde finans piyasalarının önemli bir dinamiği haline gelmiştir. Çalışma, 11 Mart 2020 ile 31 Aralık 2020 tarihleri arasındaki döneme ait güniçi ve günlük hisse senedi fiyat verilerini kullanmaktadır. Veriler, Borsa İstanbul'dan elde edilmiş olup, HFT faaliyetleri, "gün içi emir" verileri ile tespit edilmiştir. Spekülatif balonların varlığı ise Supremum Augmented Dickey-Fuller (SADF) ve Generalized Sup Augmented Dickey-Fuller (GSADF) modelleri kullanılarak test edilmiştir. Çalışma, HFT işlemlerinin balon oluşumunda önemli bir rol oynadığını tespit etmiştir. HFT işlemleri, yüksek işlem hacimleri ve hızlı işlem yetenekleriyle piyasada aşırı oynaklık ve manipülasyon yaratabilir. Bu durum, balon oluşumunun

[1] Asst. Prof., Niğde Ömer Halisdemir University, FEAS, Niğde, Türkiye, *mehmetsinancelik@ohu.edu.tr.*

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riskini artırabilir. Çalışma, finansal piyasalardaki HFT etkilerini hafifletmek için düzenleme ve denetimin önemini vurgulamaktadır. Piyasada şeffaflığı artırmayı amaçlayan düzenlemeler, yatırımcıların daha bilinçli kararlar almasına yardımcı olabilir.

Anahtar Kelimeler: *Algoritmik İşlemler; Yüksek Frekanslı İşlemler Oynaklık; Likidite; Spekülatif Balonlar*

JEL Sınıflandırması: *G12, G17, G19*

1. Introduction

Trading stocks on exchanges has changed significantly due to technological advances and regulations. As a result of these changes, it is seen that the vast majority of trading transactions are carried out by computers based on algorithms today. The type of transaction with high-speed algorithms that has a large share of transactions in the market is called high-frequency trading (HFT). High-frequency trading uses automated strategies to distribute high-volume orders in seconds (Philips, 2013). Another definition of HFT is quick and short-term orders via computers using artificial intelligence (Hasbrouck & Saar, 2013). HFT transactions make large-volume transactions in large markets and deeply affect the micro-structure of markets. Although it is stated that HFT transactions did not affect the “Flash Crash” event that occurred on May 6, 2010, this type of transaction with such a large trading volume in the market also brings many risks. HFT transactions, as an important dynamic that affects prices in the market, have the potential to trigger sudden rises and falls in the market.

This study investigates whether high-frequency trading (HFT) transactions, which have been actively applied in a developing market in a relatively recent period, lead to the formation of a speculative bubble. Developing markets offer higher returns than developed markets. However, speculative bubbles are more common in markets with higher returns. Especially after the financial globalization in the 1980s, developing markets have recorded rapid growth. Since these markets are exposed to sudden and large amounts of capital flows, there has been a sudden increase in asset prices, and it can be said that they are relatively more favorable for speculative bubbles than developed markets (Tran, 2017: 1). However, speculative bubbles that form in capital markets can be interpreted as an indicator of an unstable market. From this perspective, our study offers innovations regarding the relationship between HFT and bubbles in developing markets. Research shows that investors cause price volatility to increase with herd behavior in the market, trigger sudden rises and falls, and algorithms accelerate the formation of bubbles (Harras & Sornette, 2011; Hirshleifer, 2015). The study used both the Supremum Augmented Dickey-Fuller (SADF) and Generalized Sup Augmented Dickey-Fuller (GSADF) models to detect asset price bubbles. The study consists of an Introduction, Literature review, Data and Methodology, Empirical Results, and Conclusion sections.

The remainder of the paper is organized as follows. Section 2 presents the literature review. Section 3 describes the data and methodology. Section 4 reports the empirical findings, and section 5 concludes the paper.

2. Literature Review

The literature on the subject is given, as few studies cover both HFT transactions and bubbles. The first studies on HFT transactions investigate whether they increase liquidity (Hendershott et al., 2011; Jarnecic & Snape 2014). Over time, the effect on volatility has also been added to the studies on HFT, and the effects on the liquidity and volatility of the stock market have been investigated. The results are not one-sided but differ negatively and positively. While increasing liquidity and reducing volatility in the stock market is defined as a positive effect, reducing liquidity and increasing volatility is defined as a negative effect (Hendershott et al., 2011; Patterson 2012; Foucault et al., 2013; Hasbrouck & Saar 2013; Menkveld 2013; Biais et al. 2014; Boehmer et al. 2015; Richard et al., 2015). Some studies show that it has no effect other than positive or negative (Ekinci & Ersan, 2022). In the latest studies conducted on the Istanbul Stock Exchange, it has been revealed that it increases both liquidity and volatility (Celik et al., 2022). In addition, some studies show that HFT transactions play a market-maker role (Li et al., 2018; Baldauf & Mollner 2020; Ammar et al., 2020; Glossner et al., 2020). The bubble premium tests, initially introduced by Hardouvelis (1988), aim to measure the extra returns investors expect in the presence of bubbles. Investors need the bubble premiums to be sufficiently high to decide to stay in the market, even though they are aware that bubbles may burst. When bubbles burst, investors experience significant losses. Therefore, bubble premiums are positive and increase throughout the bubble's life. Rappoport & White (1991) also utilized this method to examine the existence of rational speculative bubbles. When examining studies related to emerging markets, research on the stock markets of Korea and India does not mention the presence of speculative bubbles (Mitra & Chaudhuri, 2016; Singh et al., 2018). Similarly, a study on the Philippines, which is an underdeveloped market, also supports the absence of speculative bubble formation (Glindro & Delloro, 2010).

3. Data and Methodology

The study method can be examined in two directions: HFT and bubbles. The detection of HFT transactions constitutes the first part of the method, while the detection of bubbles constitutes the second part. Bubble detection is explained in the applied results section. The study first detected HFT activities in Borsa Istanbul between March 11, 2020, the beginning of COVID-19, and December 31, 2020. The literature provides two methods for determining HFT activities: first, accessing HFT activity data directly, and second, detecting activities with the order book. The second method was used since there is no data repository for HFT activities in the Borsa Istanbul. The "Quick Reactions" approach was frequently used in the literature for HFT activity detection (Hasbrouck & Saar, 2013; Ersan & Ekinci, 2016). Since the Borsa Istanbul contains a large number of modification orders, modification orders were also included in the method.

HFT activities are detected with "intraday order" data. Intraday order data are organized considering the stock market trading hours of 10:00–13:00 and 14:00–18:00, which are the working hours of the Borsa Istanbul. The intraday order dataset includes all electronic messages sent to the system, their time, order identification number (identification number), date, delivery time in seconds, transaction direction (buy/sell), price, quantity, and order types. Many order messages with different quantities and speeds are sent to the stock exchange from a specific order identification number. Order data were obtained from the Borsa Istanbul "datastore".

The analysis incorporated several key control variables: firm size, trading volume, and overall market return to ensure robust estimates. The natural logarithm of market capitalization captured firm size, as larger companies might exhibit different bubble dynamics. Trading volume was assessed through the natural logarithm of daily trading activity, accounting for potentially higher volatility in liquid stocks. To control for general market trends, the daily return of the BIST-30 index was included. All daily data, including bid, ask, high, low, open, close prices, and volume, were sourced from the official Borsa Istanbul daily bulletin. Market capitalization for each stock was additionally retrieved from isyatirim.com to complete the firm-level data.

Following the seminal paper written by Hasbrouck and Saar (2013), we construct the daily HFT ratio of each stock as follows:

$$HFT\ ratio_{i,t} = \frac{Number\ of\ HFT\ order\ messages_{i,t}}{Number\ of\ all\ order\ messages_{i,t}} \tag{1}$$

where is the ratio of HFT orders for stock i on day t, defines as the daily total number of order messages for stock i on day t. is the number of order messages that satisfy the criteria of being labeled as HFT order messages.

To calculate the High-Frequency Trading (HFT) ratio, it is essential to determine the quantity of HFT order messages associated with each stock. Building upon the methodology outlined by Ekinci and Ersan (2022), HFT activity is defined as instances where more than one order message, having identical size and direction (buy/sell), is generated by the same investor within a brief timeframe—specifically, one second or less. After identifying the count of HFT order messages, this figure is normalized by considering all order messages for stock i on day t. The resulting normalized value represents the HFT ratio for each stock on a given day. We follow Barbara et al. (2020) and construct liquidity for each stock as follows:

$$\mathrm{Liquidity_{i,t}} = \frac{Ask_{i,t} - Bid_{i,t}}{(Ask_{i,t} - Bid_{i,t})/2} \tag{2}$$

where is the lowest price of stock i on day t, and   is the highest price of stock i on day t.

To capture the volatility of each stock, we adopt Garman and Klass's (1980) model as a proxy for volatility. The daily volatility proxy is calculated as follows:

$$\mathrm{Volatility_{i,t}} = \sqrt{\frac{1}{2}(\mathrm{h_{i,t}} - \mathrm{l_{i,t}})^2 - (2\log 2 - 1)\mathrm{c_{i,t}^2}} \tag{3}$$

where ci,t=log(closepricei,t) - log(openpricei,t); li,t= log(lowestpricei,t) - log(highestpricei,t); hi,t= log(highestpricei,t) - log(openpricei,t).

We will employ a Logit-Probit model to ascertain the impact of High-Frequency Trading (HFT) on the formation of market bubbles. A marginal effects analysis will be conducted to facilitate the interpretation of coefficients. Logit and Probit models are specifically designed for scenarios where the dependent variable is binary (consisting of 0s and 1s), while the independent variable can assume a range of values. It is worth noting that models with a dummy dependent variable can, in principle, be restructured as linear probability models and estimated using the Least Squares Method. However, such approaches can introduce issues of heteroscedasticity into the analysis results. Furthermore, the error term series in linear probability models typically deviates from a normal distribution. The Logit and Probit models have been specifically developed to address these inherent limitations of linear probability models. Regarding the regression model, logistic regression and marginal effects were used because our model included days with and without bubbles as 1 and 0, respectively. Ideally, we want to understand what the model is saying on the probability scale, not on the odds scale, much less on the estimation scale, the log-odds. In the probability scale, all effects are nonlinear because, conditional on covariate values, the probability must be bounded between 0 and 1. This is where numerical methods come to the rescue. We call them marginal effects in econometrics, but they come in many other names and there are different types. In a nutshell, marginal effects use model prediction for interpretation (Uğurlu, 2010: 9).

4. Empirical Results

In this section, we investigate the impact of HFT activities on the formation of stock market bubbles by detecting stock price bubbles. SADF and GSADF methods detect stock price bubble movements and dates. Rtadf-Right Tailed Augmented Dickey-Fuller Tests (Rtadf-Right Tailed Augmented Dickey-Fuller (ADF) Tests) are used to test for the presence of a bubble in financial assets. Phillips, Wu, and Yu (2011) developed the SADF test for detecting bubbles in asset prices. Phillips and Shi Yu (2015) noted that the SADF test has reduced statistical power in detecting multiple bubbles in a data set and recommended the use of the GSADF test as a generalized SADF test.

$$y_t = \mu + \delta_{t-1} + \sum_{i=1}^{k} \emptyset_i \, \Delta y_{t-1} + \varepsilon_{t,} \sim iid\ (0, \sigma^2) \tag{4}$$

The equation shows the constant μ, the exchange rate variable *yt*, the coefficient (δ) *yt*-1, the maximum lag number k, and the error term εt. The null hypothesis of the equation is that the exchange rate series contains a unit root, while the alternative hypothesis is that the series is stationary. The same equation can also be used to test for the presence of a bubble in the exchange rate series (Caspi, 2016: 491).

H0: δ =1 (No Bubble)

H1: δ > 1 (Bubble)

$$ADF = \frac{\hat{\delta}}{SE\ (\hat{\delta})} \tag{5}$$

In the equality presented in Equation 2, the numerator represents the OLS (Ordinary Least Squares) estimate of δ, and the denominator represents its standard error. When δ is defined as a fractional root in the interval [r1, r2], the sample range is expressed as 0<r1<r2<1. Here, when rw (fractional) is used for the estimation windows in the regression, rw = r2 - r1, and it is expected to be formed in the range of r0 in Eq. (5). The SADF test of Phillips, Wu, and Yu (2011) is based on the iterative calculations of the ADF statistics with a fixed starting point and expanding estimation window. Table 1 presents summary statistics of the variables.

Table 1: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Liquidity	4466	0.032	0.0203535	0.005	0.178
Volatility	4466	0.019	0.0121376	0.002	0.113
Market Return	4466	0.001	0.0166527	-0.079	0.059
HFT	4466	0.056	0.0339604	0.004	0.661
Volume	4466	19.502	0.9462221	16.951	23.362
Size	4466	23.480	0.7312813	21.059	24.712

Liquidity is calculated based on the daily trading volume of a stock. The table shows that the average liquidity is 0.032, with a standard deviation of 0.020. This indicates that liquidity is quite variable. The average volatility is 0.019, which means that volatility is 19% for each observation. The standard deviation of volatility is 0.012, indicating that volatility is also quite variable between observations. The average return is 0.001. The standard deviation of return is 0.017, indicating that return is also quite variable between observations. The average HFT activity is 0.056, which means that HFT transactions are 56% for each observation. The standard deviation of HFT activity is 0.034. The average volume is 19.502, which means that the logarithm of the volume is 19.502 for each observation. The standard deviation of volume is 0.95. The average market return is 23.480, which means that the logarithm of the market value is 23.480 for each observation. The standard deviation of the market return is 0.73. Table 2 presents the average correlations between variables.

Table 2: Correlation Analysis

	Bubble	Volume	Size	HFT	Market Return	Volatility	Liquidity
Bubble	1.0000						
Volume	0.0994	1.0000					
Size	-0.0733	-0.0088	1.0000				
HFT	0.0337	-0.0305	-0.0143	1.0000			
Market Return	-0.0043	0.0855	0.0220	0.0195	1.0000		
Volatility	0.1701	0.4588	-0.1873	-0.0099	-0.0429	1.0000	
Liquidity	0.1653	0.4668	-0.1650	-0.0095	-0.0733	0.9320	1.0000

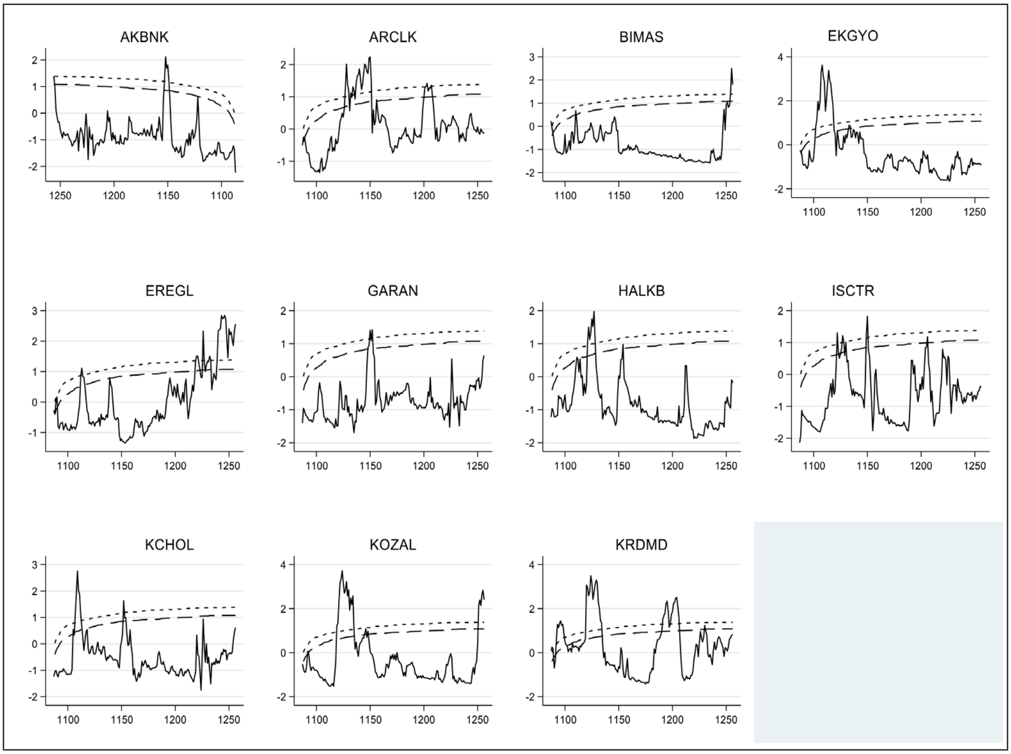
The correlation matrix presented in Table 2 is for a dataset of 4466 observations. The correlation coefficient measures the strength of the relationship between two variables. A correlation coefficient close to 1 indicates a strong relationship, while a correlation coefficient close to 0 indicates a weak relationship. The relationship between liquidity and bubble is seen as 0.1653 in Table 2. Also, a positive and weak relationship. This means that when liquidity is high, bubble formation is less likely. This is because liquidity allows market participants to buy and sell assets easily, which can help prevent bubbles from forming. We cannot say that there is a moderate relationship for this value, we can even say that there is no relationship. This means that HFT transactions may facilitate bubble formation. This is because HFT algorithms can quickly identify and exploit market inefficiencies, which can lead to price bubbles. The correlation coefficient between volume and bubble is 0.0994, indicating a weak positive relationship. This means that bubble formation may be more likely as volume increases. This is because increased trading volume can lead to greater volatility, making it more difficult for market participants to identify and exploit market inefficiencies. The correlation coefficient between size and bubble is -0.0733, indicating a weak negative relationship. This means that bubble formation is less likely when the market value is high. This is because a high market value suggests that investors are confident in the asset's value, making it more difficult for a bubble to form. The correlation coefficient between return and bubble is -0.0043, indicating a weak positive relationship. This means that bubble formation may be more likely as return increases. This is because increased returns can lead to investor optimism, making it more likely that investors will bid up asset prices. The correlation coefficient between volatility and bubble is 0.1701, indicating a moderately positive relationship. This means that bubble formation may be more likely as volatility increases. This is because increased volatility can make it more difficult for market participants to identify and exploit market inefficiencies, leading to price bubbles.

Table 3: Statistics of the Bubble Period

Panel A: number of bubble days	**AKBNK**	**ARCLK**	**BIMAS**	**EKGYO**	**EREGL**	**GARAN**	**HALKB**	**ISCTR**	**KCHOL**	**KOZAL**	**KRDMD**	**SUM**
March- December 2020	6	35	5	21	38	5	10	9	11	27	46	**213**
Panel B: number of bubble days	**PETKM**	**SAHOL**	**SISE**	**TAVHL**	**TCELL**	**THYAO**	**TKFEN**	**TTKOM**	**TUPRS**	**VAKFN**	**YKBNK**	**SUM**
March- December 2020	14	29	30	8	18	15	12	4	8	23	23	**184**
SUM bubble days												**397**

Panel A included in Table 3 shows the number of bubble days for the stocks AKBNK, ARCLK, BIMAS, EKGYO, EREGL, GARAN, HALKB, ISCTR, KCHOL, KOZAL, and KRDMD in the period from March 2020 to December 2020. The total number of bubble days in Panel A is 213. Panel B included in Table 3 shows the number of bubble days for the stocks PETKM, SAHOL, SISE, TAVHL, TCELL, THYAO, TKFEN, TTKOM, TUPRS, VAKFN, and YKBNK in the same period. The total number of bubble days in Panel B is 184. In total, the number of bubble days for all stocks is 397.

Figure 1: Panel A Stocks Bubble



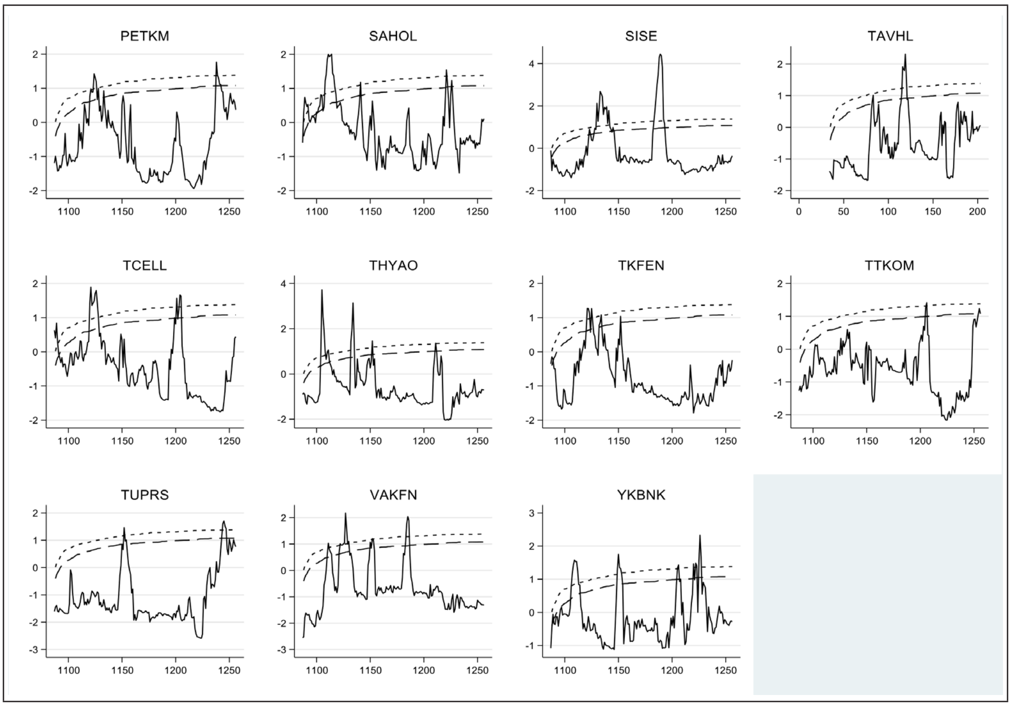
The small dashed line indicates the 95 percent level of critical value, while the large dashed line presents the 90 percent level of the critical value of the bootstrapped Dickey-Fuller test statistics. The straight line represents the BSADF test statistics. The x-axis in the graphs represents the days, while the y-axis represents the balloons. Days above the line starting from the y-axis indicate days with balloons.

Table 4: Logistic (Marginal Effect) Regression Results

Number of obs.= 3718						**LR chi2 (6) = 104.08**
Loh likelihood= -1211.060						**Prob > chi2 = 0.000**
Bubble	**Dy/dx**	**Std. Err.**	**Z**	**P>|z|**	**[95% Conf.]**	**[Interval]**
HFT	0.205	0.143	2.12	0.034	0.023	0.587
Volume	0.010	0.005	1.89	0.059	-0.000	0.021
Size	-0.017	0.006	-2.71	0.007	-0.029	-0.004
Liquidity	0.570	0.631	0.90	0.366	-0.666	1.807
Volatility	2.204	1.096	2.01	0.044	0.055	4.353
Market Return	-0.061	0.318	-0.19	0.847	-0.685	0.563
Cons.	0.455	0.939	-0.38	0.703	0.008	25.910

Table 4 presents the results of a logistic regression analysis investigating the factors that affect the probability of bubble formation for stocks traded on the Borsa Istanbul (BIST) during the period from March 2020 to December 2020. Table 4 presents the marginal effect of each independent variable on the probability of bubble formation. HFT activities increase the probability of bubble formation. This is because HFT transactions can disrupt market flows and lead to price bubbles, facilitating bubble formation. The coefficient value is 0.205, and the significance value is 0.034. This indicates that HFT activities could increase the probability of bubble formation by 20.5%. The increase in volatility increases the probability of bubble formation. The coefficient value is 2.204, and the significance value is 0.044. This indicates that a 1% increase in volatility could increase the probability of bubble formation by 22.04%.

Figure 2: Panel B Stocks Bubble



The small dashed line indicates the 95 percent level of critical value, while the large dashed line presents the 90 percent level of the critical value of the bootstrapped Dickey-Fuller test statistics. The straight line represents the BSADF test statistics. The x-axis in the graphs represents the days, while the y-axis represents the balloons. Days above the line starting from the y-axis indicate days with balloons.

HFT activity increases the probability of bubble days because HFT can create excessive price volatility and market manipulation. HFT firms can exploit market inefficiencies with their high trading volumes and quick trading capabilities, contributing to bubble days' formation. Volume increases the probability of bubble days because the probability of excessive price volatility and market manipulation increases in high-volume trading. In high-volume trading, large amounts of money or stocks entering the market can create excessive price volatility and create bubble days. Companies with a large market capitalization have stronger financial performance, better governance, and lower debt ratios. These factors make companies with large market capitalization less susceptible to the formation of bubble days. In periods of high volatility, price movements in the market become more unpredictable, which makes them more susceptible to excessive price volatility and market manipulation.

5. Conclusions

Stock market bubbles are days when a stock price rises unjustifiably extreme, beyond normal price movements. Bubbles often occur during periods of excessive price volatility and market manipulation. The formation of bubbles can pose significant risks for investors. During bubbles, stock prices can rise far above their fundamental value. This can lead to losses for investors. This study examines the factors that affect the formation of bubbles in the Turkish stock market. The study uses daily stock price data from the period from March 2020 to December 2020. The data was obtained from Borsa Istanbul. The study's findings are consistent with previous research on bubble formation in financial markets. Tran (2017) found that sudden and large influxes of money into markets can trigger bubble formation. Harras and Sornette (2011) found that investor herd behavior can increase price volatility, triggering sudden rises and falls, and that algorithms can accelerate bubble formation. Our study findings add to this growing body of research by providing evidence of the role of HFT in bubble formation in emerging markets.

High-frequency trading (HFT) transactions have the potential to create excessive price volatility and market manipulation. HFT firms, with their high trading volumes and quick trading capabilities, can manipulate the market and contribute to the formation of bubble days. Analyses have shown that HFT activity, volume, size, and volatility are important factors in the formation of bubble days in the stock market. The increased likelihood of bubble days with HFT activity is especially evident during periods when more unusual price movements are observed in certain stocks. This is because high-frequency trading increases volatility in the market and triggers the possibility of manipulation. HFT firms can also buy and sell large amounts of stocks in the market, which can affect price movements and contribute to the formation of bubble days. Investors should be more careful during periods when HFT activity is intense in certain stocks. During these periods, volatility in the market may increase, and the risk of manipulation may rise. Risk management strategies should be updated to account for these risks. The results of this study highlight the importance of regulation and supervision in balancing the effects of HFT in financial markets. Regulations aimed at increasing transparency in the market can help investors make more informed decisions.

Statements and Declarations

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