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Behavioral Biases and Market Fluctuations:

An Empirical Study of Herding and Volatility in Vietnam

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Abstract

Purpose

This research assesses the intensity and presence of the herding behavior in the Vietnamese stock market and its influence on the trading activity and price volatility. Given the dominance of retail investors and limited market transparency, the study examines how collective investor sentiment impacts volatility before, during, and after the COVID-19 pandemic.

Design/methodology/approach

Using intraday transaction data from the Ho Chi Minh Stock Exchange (HOSE) between March 2019 and January 2025, the herding intensity is assessed through Patterson and Sharma's (2006) run-based statistic. The GARCH(1,1) approach is utilized to explore how herding and trading volume influence market volatility, with the dataset divided into three sub-periods: pre-COVID, during COVID, and post-COVID. Stationarity and approach robustness are confirmed by utilizing the Augmented Dickey-Fuller (ADF) test.

Findings

The results confirm statistically strong herding behavior, particularly during the COVID-19 period, as both buyer (Hu) and seller (Hd) herding intensities frequently fall below the −1.96 threshold ($p < 0.01$), indicating significant directional clustering. Trading volume and herding intensity both significantly increase conditional market volatility ($p < 0.01$), with volatility remaining highest during the pandemic and moderating but still elevated in the post-COVID period. These patterns show that intraday herding measures can serve as early-warning indicators of volatility spikes in a retail-dominated emerging market.

Originality/Value

This research is the first to integrate Patterson–Sharma intraday herding metrics with a GARCH(1,1) volatility model to study the Vietnamese stock market across pre-crisis, crisis, and post-crisis regimes. It provides rare intraday evidence from a developing market dominated by retail investors and quantifies how directional and zero-return herding affect volatility dynamics. By treating Hu, Hd, and Hz as behavioral risk indicators, the study contributes to Decision Sciences by offering empirically grounded analytics that support decision-making under ambiguity for market makers, regulators, and investors.

Keywords: Herding behavior; Trading volume; Market volatility; GARCH(1,1); Behavioral finance; Vietnam stock market; COVID-19

JEL Classifications: G12; G14; G15; C58

1. Introduction

As mentioned by Fama (1970), the efficient market hypothesis (EMH) holds that traded asset prices, such as stocks, bonds, and real estate, fully reproduce all available information in the markets. However, in reality, investors often diverge from the 'rational' assumptions of conventional financial theories. Herding behavior is a common phenomenon in financial markets, where investors imitate the actions of others rather than conducting their own independent analysis. Some observers express concern about the unfavorable influence of herding on the significant movement of stock prices. Herding behavior frequently leads to asset mispricing, wherein securities deviate from their intrinsic values due to fluctuations driven by sentiment or external factors, rather than fundamental ones. Several studies support the concern that the existence of herding can exacerbate market fluctuation and destabilize financial markets (Demirer & Kutan, 2006; Hashmi et al., 2021b; Wei et al., 2024).

Significantly, studying herd behavior not only remains an interesting area of inquiry for its own sake but also carries practical significance for the fields of decision-making and risk management. In this regard, detecting signs of behavior can help both investors and regulators prepare for upcoming waves of volatility.

The Vietnamese stock market was a nascent market; however, there had been continuous improvement in the structure of that capital market, and important bases had been created. As of November 13, 2024, the total market capitalization was equivalent to 69% of the 2023 GDP, compared to 27% of GDP in 2015 (GDP at current prices), and reached over 5.8 million billion VND. However, in developing markets such as Vietnam, the less transparent environment, stemming from factors like weaker reporting supplies, lower accounting standards, loose regulatory implementation, and costly information gathering, information cascades and the herding behaviors are more likely to arise. Furthermore, as information may be disclosed and absorbed more slowly, momentum investing strategies may yield higher returns. Unlike mature markets with higher institutional participation, emerging markets are often more susceptible to behavioral biases that amplify volatility, making it imperative to have more empirical research to explore the nuances of herding behavior in this context (Bikhchandani & Sharma, 2000; Chang, 2020; R. Gohar et al., 2022a, 2022b; Noman et al., 2023; Privara et al., 2025).

Data from the VSDC (Vietnam Securities Depository and Clearing Corporation) shows that as of November 30, 2024, the number of domestic individual investor accounts was over 9 million, dominating with a rate of 99.8% of the total number of investment accounts in the Vietnamese stock market. Meanwhile, the number of domestic institutional accounts was 17,599 (accounting for 0.2%). However, this growth also brings about speculative issues, especially in the 2020-2021 period, when many people tend to engage in speculative short-term trading to earn high profits in a short time. According to the World Bank (WB) in the August 2024 Macro Monitoring Report, the Vietnamese stock market is lacking in investor structure diversity. The individual investors' large proportion is prone to negatively impacting the market, as individual investors often invest based on sentiment, have a herd mentality, lack in-depth knowledge of stocks and the market, and often have a short-term vision (B. H. Chang et al., 2022; B. H. Chang et al., 2024; Gohar et al., 2023a, 2023b).

Several researchers have found the existence of herding and different patterns depending on various market situations in the Vietnamese stock market (Bouri et al., 2019; Dao & Tu, 2014). Recently, Dam et al. (2023) examined herding behavior in the Vietnamese stock market from January 2018 to December 2021 and found evidence of increased herding behavior during the COVID-19 period. Current studies on herding behavior in Vietnam focus only on the Ho Chi Minh City Stock Exchange (HOSE), and very few examinations have evidence of herding on the Hanoi Stock Exchange (HNX). Studies on the herding behavior in the Vietnamese stock market mainly emphasize the general market, rather than individual sectors (W. Ali et al., 2022; Fan et al., 2025; Mishra et al., 2025; Salman et al., 2023b; E. Uche et al., 2022b; X. V. Vo & Phan, 2017). This limits our understanding of how herding behavior affects different sectors of the market.

Furthermore, all of these studies rely on the end-of-day closing prices. This makes it more difficult to analyze the intraday movements. At the same time, the intraday movements may contain significant information about the degree of influence of herding. Future research studies need to utilize the intraday transaction data analysis technique to determine the degree of herding influence on the Vietnamese stock market's volatility accurately (W. Ali et al., 2022; Patterson & Sharma, 2006). Recent researches also utilized the novel econometric methods to assess the complex financial market association and ambiguity dynamics (Aldawsari et al., 2024; Chen et al., 2024; Mei et al., 2024b; Tu et al., 2024; Uddin et al., 2025).

Given the context of the background information, the Vietnamese stock market poses a unique case for analysis regarding the phenomenon of herding on the stock market. The factor of dominance by retail investors in the Vietnamese market and the lack of transparency in the market provide the required conditions for investor herding to have a strong influence on the market.

Although some research has investigated the phenomenon of herding in the context of international markets for different countries, the body of evidence in the case of the emerging economy of Vietnam needs to be developed. The existing examinations have largely concentrated on the issue of herding at the market level when dealing with daily frequencies of trading activity. At the same time, there was a lack of consideration of the short-term nature of the market processes in order to more accurately reflect the herding influence levels on the fluctuation of the market. To correct the identified deficits of the existing studies, the following research intends to explore the effect of herding levels of investors and trading volumes on the volatility of the Vietnam Stock Market.

This research aids original value by integrating high-frequency intraday transaction data with the Patterson and Sharma (2006) run-based statistic to assess the herding intensity—a method not previously employed in the Vietnamese stock market. Moreover, the study includes the literature where the herding intensity indices are included in the GARCH (1, 1) volatility framework to gain an in-depth perspective on the relationship between behavioral effects and volatility, including the period prior to COVID-19, the period during COVID-19, and post-COVID-19 era. An innovative point of this study is the independent consideration of neutral herding behavior (Hz), negative herding behavior (Hd), and positive herding behavior (Hu), providing a more refined approach to understand the psychological behavior of investors depending on changes in market conditions. This indicates that the intraday herding intensity index is a precursor to instability, providing a behavioral warning signal. By identifying the herding intensity during the intraday period as an actual behavioral signal, the paper introduces an early warning signal that can be used in detecting volatility. This helps the investors in taking corrective measures regarding risk exposure.

Finally, this study makes an important contribution to Decision Sciences, in general, as it provides behavioral metrics based on empirical evidence for decision-making under ambiguity for market makers, regulators, and investors (Almazyad et al., 2024; Li et al., 2024; Xing et al., 2024).

By linking intraday herding measures directly to volatility dynamics, the study provides decision-oriented metrics that can be embedded into risk management, surveillance, and early-warning systems in emerging equity markets. The remainder of the article is divided as follows: Section 2 reviews the literature and theoretical framework on herding behavior and volatility in the Vietnamese stock market. Section 3 presents the data collection and research methodology. Section 4 discusses the empirical findings, and Section 5 summarizes the conclusions and recommendations.

2. Theoretical Background and Literature Review

2.1.Theoretical Background

2.1.1. Behavioral Finance and Herding

Behavioral Finance studies how human psychology affects investment behavior and market results, breaking away from the notion of perfectly rational agents (Sewell, 2007). One of the common behavioral biases is the "herd effect" in which investors mimic other people's behavior instead of conducting their own research (Lakonishok et al., 1992). According to Prospect Theory, humans tend to be more fearful of losses compared to gains, prompting them to conform to the majority to mitigate risks (Tversky & Kahneman, 1991).

Herding may bring about vulnerability in the market by promoting asset misvaluation, speculation, and higher market volatility, especially in crisis periods like the dot-com era (W. Ali et al., 2022; Bikhchandani & Sharma, 2000; Maydybura et al., 2023). Herding behavior is widespread in emerging economies such as Vietnam because retail investors dominate the market, and most investors tend to depend on hearsay and popular opinions rather than their own evaluations.

Christie and Huang (1995) were among the first authors to estimate the herding by assessing whether the return dispersion decreases throughout the extreme market anxiety periods. They developed the CSSD (Cross-Sectional Standard Deviation) approach as a dispersion estimate around the return of the market. The CSSD at the time is described as:

$$CSSD_t = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N} (R_{i,t} - R_{m,t})^2},$$

where stock returns' cross sectional standard deviation is indicated by $CSSD_t$ at time t. $R_{i,t}$, $R_{m,t}$, N, and t represents the stock return i at time t, average market return at time t, stock's total number in the market polio, and indexes time, respectively. To assess whether the herding increases throughout extreme market movements, Christie and Huang suggested the following regression approach:

$$CSSD_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \epsilon_t,$$

where α is a constant term, $D_t^L = 1$ if the return of market lies in the lower extreme tail, 0 otherwise, and $D_t^U = 1$ if the return of market lies in the upper extreme tail, 0 otherwise. A substantially unfavorable β_1 and β_2 denote that the dispersion return declines during the extreme situations of the market, thus signaling the herding behavior.

However, the CSSD approach offers valuable information; it has limitations, especially its emphasis on only extreme market situations. To resolve these limitations, E.C. Chang et al. (2000) suggested a more resilient method by developing the CSAD (Cross-Sectional Absolute Deviation) as a return dispersion estimate. The CSAD at the time is described as:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N} |R_{i,t} - R_{m,t}|,$$

where $CSAD_t$ presents the return deviation's absolute value at time t (Cross-Sectional Absolute Deviation), measuring the dispersion of returns. $R_{m,t}$ signifies the absolute market return of N assets in the market portfolio at period t. $R_{i,t}$ indicates the return of asset (or cryptocurrency) i at period t. E.C. Chang et al. (2000) also suggested a nonlinear regression approach to assess how dispersion alters with market movements:

$$CSAD_t = \alpha + \gamma_1 \left|R_{m,t}\right| + \gamma_2 R_{m,t}^2 + \epsilon_t.$$

Under rational asset pricing, dispersion return should increase linearly with the returns of the market. Thus, a substantially unfavorable γ_2 denotes that the dispersion does not surge proportionally with the returns of the market, suggesting that investors are congregating towards market agreement. This asymmetric pattern is interpreted as evidence of herding behavior.

2.1.2. Stock Volatility

Volatility refers to fluctuations in asset prices over time and reflects the level of uncertainty associated with investment risk (Hashmi & Chang, 2021; Hashmi et al., 2021b, 2022; Poon & Granger, 2003; Syed et al., 2019). It has a very important application in portfolio management, risk evaluation, and the valuation of derivatives like options and futures. It becomes important to measure volatility precisely for effective portfolio management and risk evaluation. However, conventional econometric models tend to assume constant variance, which cannot account for the changing variance of the financial markets.

ARCH and GARCH Model: Foundations and Relevance in Volatility Analysis

To address the limitations of constant-variance assumptions, Engle (1982) developed the ARCH (Autoregressive Conditional Heteroskedasticity) approach, and Bollerslev (1987) enhanced it to GARCH Generalized Autoregressive Conditional Heteroskedasticity). The GARCH (1,1) method efficiently captures variations clustering-periods of low or high volatility occurring consecutively, and remains a standard approach due to its simplicity and predictive strength in volatility valuation.

GARCH (1,1) Approach

The investigation makes use of the GARCH methodology in order to assess the effect of herding on volatility in the Vietnam Stock Market. The methodology helps in effectively explaining the phenomenon of volatility clustering in the market. Herding movements in the market accentuate the effect of volatility. The easy methodology is helpful to obtain accurate results from the market without having a large processing burden (W. Ali et al., 2022; D. A. Hsieh, 1989; X. Wang et al., 2024). The chosen methodology has made it possible to use the GARCH (1,1) model in the study.

2.2.Literature Review

2.2.1. Literature on Herding Behavior and Volatility

Instability in the stock market is affected by various macroeconomic, financial, and behavioral factors. The empirical literature reveals that volatility is associated with macroeconomic factors like GDP, exchange rate, unemployment, and foreign debts (Vychytilová et al., 2019). It is also influenced by monetary factors such as money supply, interest rate, and inflation (Corradi et al., 2012). The behavior of the market is also affected by the firm's diversification, price-to-earnings ratio (P/E ratio), earnings per share (EPS), return on assets (ROA), and return on equity (ROE) (Stockdale, 2014; Das and Ramji, 2021; T. N. L. Nguyen and V. C. Nguyen, 2020). Industrial production and macroeconomic indicators also play an important role in creating volatility (Waqas et al., 2015; Chang et al., 2024a; Chen et al., 2024; Mei et al., 2024b; Tu et al., 2024). Extremist events like the coronavirus disease (COVID-19) pandemic and the 2008 financial crisis further increase volatility and uncertainty in the stock market (Hashmi et al., 2021a; Rehman, 2024; Uche, Chang, and Effiom, 2022). Behavioral factors like herd behavior and investor sentiments may also contribute to volatility without any fundamental changes (Abaidoo & Agyapong, 2021; Peng et al., 2022).

Early studies about herding behavior yielded conflicting findings. According to Lakonishok et al. (1992) and W. Ali et al. (2022), institutional investors demonstrate herding behavior without causing instability in price movements, and according to Bowe and Domuta (2004), relying on the results of Lakonishok et al. (1992) and B.H. Chang et al. (2023), foreign investors display more pronounced herding behavior without any increase in price volatility. Christie and Huang (1995) found no evidence of herding behavior among U.S. investors, whereas E.C. Chang et al. (2000) detected herding among Asian investors but did not find any in developed countries. Recent studies indicate that herding behavior is more common in emerging markets (Imane et al., 2023; Gong et al., 2023), although it is also present globally (Chiang & Zheng, 2010).

Herding usually takes place during times when there are severe market situations and crises (Aharon, 2021; Economou et al., 2018; Stavroyiannis & Babalos, 2017). During the period of the COVID-19 pandemic, high levels of uncertainty triggered panic reactions, thereby creating volatility (B.H. Chang, 2020; Gherghina & Constantinescu, 2024; Gohar, Salman et al., 2023; Lu et al., 2023; Privara et al., 2025). Similar phenomena were found in the market for cryptocurrencies (Yarovaya et al., 2021). Regarding Vietnam, information about herding is still scarce; however, research confirms that herding exists in conditions of both rising and falling markets (Salman et al., 2023a; Kallinterakis, 2007). Herding has been confirmed in several studies using the dispersion approach in various periods (Dao & Tu, 2014; Vo & Phan, 2017; Chi & Quynh, 2024; T. M. T. Nguyen, 2022), while Dam et al. (2023) find herding mainly under normal market conditions in HOSE and HNX.

Behaviorally, herding results from imitation rather than independent decision making among investors, thus generating non-rational price movements (S.F. Hsieh, 2013; Puckett & Yan, 2009). The phenomenon is more pronounced during times of uncertainty and diminishes as markets become stable (Bekiros et al., 2017; Blasco et al., 2012). In addition, herding and volatility exhibit a reciprocal influence since the former is intensified by uncertainty and results in the predominance of behavioral over fundamental approach to asset pricing, especially within high-risk setting (Akerlof and Shiller, 2010; Stockhammer and Grafl, 2010). Specifically, herding and uncertainty stimulate one another with increasing effectiveness in high-risk conditions (Zheng et al., 2015; Jindal et al., 2024; Bagadeem et al., 2024; Lakshman et al., 2013; Mei et al., 2024a). Nonetheless, a different view on the correlation between volatility and herding exists, as some researchers argue that the former decreases because of the latter but increases within individual companies (Lobão & Serra, 2007; Balcilar et al., 2014; Litimi et al., 2016), whereas another school claims that herding does not lead to market volatility (Huang et al., 2015). Finally, the literature has experienced significant advancements in methodology, which can be seen in contributions of W. –K. Wong and M.T. Pham (2026a, 2026b) to the modeling of panel data. Furthermore, Chan and Wong (2026) and W. –K. Wong and Chan (2026) have introduced innovative tools for analyzing portfolio risk and investment analysis.

2.2.2. Volatility and Trading Volume

Trading volume is defined as the number of trades that take place within a given period in a market and has been extensively investigated in terms of volatility. The theory for this relationship is founded on the hypothesis of Mixture of Distribution (MDH), which proposes that there exists a positive relationship between trading volume and return volatility because of the arrival of information (Clark, 1973). Likewise, the hypothesis of Sequential Information Arrival (SIAH) also provides an explanation of this positive relationship through the gradual incorporation of information into prices (Copeland, 1976).

Most empirical research backs up this association. In particular, Brailsford (1996), employing the GARCH(1,1) model, proves the connection between trading volume and volatility clusters as well as large swings in prices. The same conclusion was drawn by A.H. Ali et al. (2005) when analyzing the Kuala Lumpur Stock Exchange and by Pati (2008), who proved that expected and unexpected trading volumes contribute to increased volatility, but unexpected volumes affect volatility more strongly. Ané and Ureche-Rangau (2008) further confirm the similarity in short-run dynamics but differences in long-run trends between volume and volatility.

Nevertheless, there are studies that have found the inverse correlation between volume and volatility. The studies conducted by Tauchen and Pitts (1983) and Jin et al. (2025) indicate that this can be explained by inefficiencies in markets. This viewpoint is confirmed by the studies made by H. Wang (2004), Ureche-Rangau and Rorthays (2009), Boyacıoğlu and Avci (2010), and Mougoué and Aggarwal (2011). Specifically, H. Wang (2004), applying the IDT theory, concludes that informed trading raises trading volume and lowers volatility afterward. Asymmetric information and market structure were also identified by Ureche-Rangau and Rorthays (2009) and Boyacıoğlu and Avci (2010) as factors that influence the volume-volatility connection. Generally, empirical research demonstrates that the relationship under consideration is complicated and depends on various circumstances. Most studies concerning the Vietnamese stock market prove a positive correlation between trading volume and volatility. For example, Truong et al. (2022) have discovered that trading volume in VN INDEX futures has a significant effect on spot market volatility on the HOSE both in the short-run and in the long-run.

2.3.Hypothesis Development

As per herd behavior, an investor may ignore his/her own private information and rely on the information available in the market, which leads to the synchronization of order flow, thereby causing co-movements of returns (Bikhchandani & Sharma, 2000; Christie & Huang, 1995). As the synchronous trading speeds up during times of uncertainty, the process of price discovery is hindered, resulting in increased volatility because of the cycles of trading that depend on sentiment and not on information. The process can be observed during crisis regimes in emerging markets (Chiang & Zheng, 2010; Demirer & Kutan, 2006).

The formalized hypotheses stated are as follows:

H1: *Directional herding (Hu, Hd) significantly amplifies market volatility in the Vietnamese equity market.*

H2: *Downward herding (Hd) exerts a stronger volatility effect than upward herding (Hu), reflecting asymmetric panic-driven selling responses.*

H3: *Zero-return clustering (Hz) increases volatility, albeit at a lower magnitude than directional herding.*

H4: *Trading volume positively and significantly contributes to volatility under all market conditions.*

H5: *The volatility-enhancing impact of the herding is stronger during the COVID-19 period and exhibits persistent continuation in the post-crisis phase.*

3. Data and Methodology

3.1.Data Collection

For the purpose of obtaining an accurate estimation of the presence of the herding effect as well as market volatility, two distinct data frequencies will be used in this research. The first one is minute-by-minute tick-by-tick transaction data for the Vietnam's Ho Chi Minh Stock Exchange (HOSE), which will be used to distinguish between the seller-led transactions and the buyer-led transactions and to compute the Patterson and Sharma (2006) herding intensity index (Hu, Hd, Hz). High frequency intra-day data is ideal for measuring runs and directional trades. In comparison, the second type of data frequency is the daily closing price of the VNINDEX, which will be used to measure market return as well as market volatility through GARCH(1,1).

The data period covers from March 4, 2019, to January 7, 2025, with 1458 daily returns and volume data entries for each. The intra-day transactions data are provided on a minute-by-minute basis for the entire period. Clearly defining the intra-day (tick-by-tick) data from daily data is crucial for consistent application in behavioral analysis and volatility modeling.

This research employs a set of important variables for examining the interactions between trading volume, herding behavior, and market conditions in the Vietnamese stock market. Herding behavior can be determined using three measures developed from tick data per minute: Hu for buyer herding intensity, Hd for seller herding intensity, and Hz for zero return herding intensity. Such measures provide evidence on whether the trades exhibit herd behavior toward moving in the same direction or staying around the same level that does not affect the price level. The daily return of VNINDEX can be calculated using the closing prices of VNINDEX as the important variable in studying volatility. Market volatility—central to the research—is taken from the conditional variance assessed through the GARCH(1,1) approach. To account for short-term movements in returns, the previous day's return is also included. Together, these variables deliver a clear structure for assessing how shifts in herding behavior and trading volume shape volatility in the market.

3.2.Methodology

3.2.1. Measurement of Herding Intensity

Since the Cross-Sectional Absolute Deviation (CSAD) procedure can only assess for the presence of the herding behavior, this study uses the statistics developed by Patterson and Sharma (2006) to examine the herding intensity. Previous research on herding behavior has utilized a range of methodological instruments to measure collective investor decision-making, such as measuring return dispersion, short-run return patterns, and market-level behavioral indicators. These research instruments have been used to study herding in equity, integrated, as well as alternative asset markets to measure directional as well as crisis-related herding effects (Ajaz & Kumar, 2018; Batmunkh et al., 2020; Kudryavtsev, 2019; Munkh-Ulzii et al., 2018; Vieito et al., 2024). In addition, other research works have also focused on behavioral asymmetry, institutional decision-making, as well as uncertainty-related herding behavior (Cakan et al., 2019; Lin et al., 2015), while a bibliometric study indicates the development as well as diversification of herding research instruments over time (Choijil et al., 2022). In addition, based on the aforementioned research works, the present research work utilizes an intraday run-based approach to measure herding, thereby facilitating a direct measurement of herding intensity.

The Patterson and Sharma (2006) statistic assesses the herding intensity by the number of runs, which is a random variable that can be stated as follows:

$$X_{i,j,t} = \frac{(r_i + 0.5) - np_i(1 - p_i)}{\sqrt{n}},$$

where r_i indicates the number of runs of type i (up, down, or zero), n is the total number of transactions performed on stock j on day t, 0.5 is a parameter to adjust for discontinuity, and p_i is the probability of finding a run of type i.

The Patterson and Sharma (2006) method is based on measuring runs – that is, consecutive sequences of buy, sell, or no-change transactions. If herding behavior occurs, the expected number of runs will be higher than the actual number of runs, because investors tend to mimic each other's behavior rather than making independent decisions. For statistically significant results, the herding intensity must have a negative value to indicate a systematic tendency to mimic the behavior of others.

In asymptotic conditions, the statistic has a mean of zero and a variance equal to the outcomes of the following expression:

$$\sigma^2{}_{i,j,t} = p_i(1 - p_i) - 3p_i^2(1 - p_i)^2.$$

The herding intensity index is measured as follows:

$$H_{i,j,t} = \frac{X_{i,j,t}}{\sqrt{\sigma^2{}_{i,j,t}}} \sim N(0,1),$$

where we take one of three different values depending on whether the transaction is due to buyer herding intensity (positive return, Hu), seller herding intensity (negative return, Hd), and herding intensity when keeping the price unchanged (zero return, Hz).

This implementation follows Patterson and Sharma (2006) but uses an additional $\sqrt{n}$ normalization for numerical stability; the standardization by $\sigma^2_{i,j,t}$ ensures that $H_{i,j,t}$ remains asymptotically standard normal.

If investors are involved in herding activities systematically, the indicator value will be adverse and statistically substantial because the actual number of starting sequences (runs) will be lower than expected (Patterson & Sharma, 2006). Similar to the focus on the decision-oriented herding framework in the prior studies, the directional/herding and non-directional/herding effects are analyzed separately in this paper in order to consider the asymmetry in the responses to different market conditions.

3.2.2. Return Measure

The formula for calculating daily returns is a common tool in finance, used to measure the price volatility of a financial asset from one day to the next.

Daily return equation:

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}},$$

where P_t is the value of the asset at the end of the current trading day, and P_{t-1} is the value of the asset at the end of the previous trading day.

3.2.3. Trading Volume

Trading Volume: This refers to the activity of the market since the number of stocks being traded in a given period measures market activity. Market efficiency, price discovery, and liquidity in the market depend on the trading volumes. A high trading volume suggests a highly active market where the prices change less, while a low trading volume may suggest a less liquid market with high transaction costs (Karpoff, 1987). To simplify the analysis of the data, the natural logarithm of the trading volume (ln_volume) can be used. The calculation is as follows:

$$ln\_volume = ln(V_t),$$

where V_t denotes the total number of shares traded that day, and *ln* is the natural logarithm (logarithm with base e, where e ≈ 2.71828).

3.2.4. GARCH (1,1) Technique with external variable: Measure the impact of herding behavior & trading volume on stock price volatility

Based on the research variables we've created, this research uses the GARCH(1,1) technique by Bollerslev (1987) to see how herding intensity affects changes in market volatility. The GARCH(1,1) technique, which was first presented by Engle (1982) and Bollerslev (1986), is shown in the following equations:

$$R_t = \lambda_0 + \lambda_1 R_{t-1} + \varepsilon_t, \#(1)$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2, \#(2)$$

where $\omega > 0, \alpha \geq 0, \beta \geq 0, r_t$ is the stock return at time *t*, calculated as $r_t = \frac{P_1 - P_0}{P_0}$, with P_1 and P_0 being the stock prices at time t and $t-1$. λ_1 indicate the coefficient of the lagged return r_{t-1}. λ_0 is the constant in the mean equation. σ_t^2 denotes the conditional variance at time t. ω indicates the constant in the variance equation. ε_t denotes the error term. ε_{t-1}^2 is the lagged squared residual (ARCH term), and σ_{t-1}^2 is the lagged conditional variance (GARCH term).

The size of the parameters tells us about the short-term impact of time-series fluctuations. If the sum of these two parameters is close to 1, shocks will affect stock price volatility in the long term: the variance is finite, and the volatility series will gradually stabilize over time. In this research, the basic GARCH (1, 1) technique is adjusted by adding variables Herding Intensity H_t and Logarithm of Trading Volume $ln(volume)$, which represents herding behavior (Hu, Hd, Hz) and trading volume in both the mean equation and the variance equation, as shown below:

$$R_t = \lambda_0 + \lambda_1 R_{t-1} + \varepsilon_t + \lambda_2 H_t + \lambda_3 ln\,(volume)_t + \epsilon_t, \quad (3)$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma_1 H_t + \gamma_2 ln\,(volume)_t, \quad (4)$$

where $\omega > 0, \alpha \geq 0, \beta \geq 0$ and $\alpha, \beta, \varpi, \gamma_1, \gamma_2$ are all coefficients estimated from the model and H_t indicates the herding intensity (H_u , H_d , H_z). To ensure the model works effectively, it's necessary to follow a process with these important steps:

3.2.5. Unit Root Test

In financial econometrics, the time series must be stationary. This suggests that the series should not have a tendency to grow in the positive or negative direction. There would not be any bias in the statistical projections. This happens when:

$$\alpha + \beta < 1.$$

In the above equation, if $\alpha + \beta < 1$, the variance is finite, and the volatility series will gradually stabilize over time, and if $\alpha + \beta \approx 1$, the model shows "persistence," meaning the volatility tends to continue for a long time.

In order to thoroughly conduct stationarity testing in this study, several complementary tests are employed to test for stationarity. Namely, the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests are adopted to test for the null hypothesis of a unit root, whereas the KPSS test is utilized to test for the null hypothesis of stationarity. Furthermore, the Zivot-Andrews test is performed to accommodate for the possibility of an endogenous structural break due to the COVID-19 period. The above tests are performed on the important variables, which include the VNINDEX return series as well as the herding intensity indices (Hu, Hd, and Hz).

The latest econometric evidence indicates that spurious-like statistically significant relationships can appear between I(0) variables if persistence, serial dependence, or volatility clustering is not taken into consideration. Specifically, it turns out that regression analysis of stationary yet persistent series can produce spurious-like significance caused by similar dynamic properties rather than actual economic relationships (Cheng et al., 2021, 2022; W. K. Wong, Cheng, & Yue, 2024). It is especially true when dealing with financial time series whose returns or behavioral measures tend to demonstrate a high degree of temporal dependence. The latter was confirmed to be the case both with correlation and regression, as well as in cases of correctly conducted stationarity tests, as demonstrated by W.-K. Wong and M.T. Pham (2022a, 2022b, 2023a, 2023b, 2025a, 2025b) and W. K. Wong, Cheng, and Yue (2024). In this context, in view of a high degree of temporal dependence of financial series, valid inference calls for conditional modeling rather than stationarity tests.

In tackling this problem, the current analysis steers clear of static regression models and opts for a dynamic GARCH (1,1). Through incorporating conditional variance and volatility dynamics, the GARCH approach allows for serial correlation that might otherwise cause spurious relationships to arise from stationary regressions. The measures for herding behavior and trade volumes are considered as exogenous variables in the conditional model, thus enabling the estimation of their marginal impact on explaining return dynamics. While all variables are found to be stationary through various unit root tests, stationarity per se is not taken to be sufficient for proper inference.

4. Empirical Findings

4.1. Descriptive Statistics of the Variables: Herding Intensity and Trading Volume

By examining indicators such as mean, standard deviation, and maximum and minimum dispersion values, it can better comprehend the distribution of each variable, as well as how they relate to each other in the dataset.

4.1.1. Herding Intensity Index

The descriptive statistics of the herding intensity of the VNINDEX are summarized in Table 1 below:

Table 1: Descriptive Statistics of the Herding Intensity (H_t)

Variables	Observation	Mean	Median	Minimum	Maximum	Std. Dev.
Hu	1458	-2.088	-1.961	-8.604	4.600	2.240
Hd	1458	-2.135	-1.983	-8.858	4.350	2.230
Hz	1458	-1.752	-1.708	-4.282	-0.386	0.532

Note: H_t indicates the herding intensity derived from the Patterson-Sharma (2006) statistics, where the buyer, seller, and the zero-return are indicated by H_u , H_d, and H_z, accordingly. The herding behavior is represented statistically substantial by the values of $H_t < -1.96$, aligned with equation (H).

Based on the criterion $H_{i,j,t}$ < -1.96 to determine the presence of herding with statistical significance, it can be seen that the average values of Hu (-2.088) and Hd (-2.135) indicate that herding exists significantly when the market rises or falls. Hz has an average value -1.752, reflecting a weaker overall herding level compared to each individual state.

4.1.2. Trading Volume

Based on the descriptive statistics in Table 2, it can be seen that trading volume has a moderate level of volatility during the study period. The mean (13.158) and median (13.337) are quite close, indicating that the data distribution is relatively balanced. However, with a standard deviation of 0.592, indicating that the market maintains a certain level of stability in trading volume.

Table 2: Descriptive Statistics of the Trading Volume

	Observation	Mean	Median	Minimum	Maximum	Std. Dev.
Ln_Volume	1458	13.158	13.337	11.580	14.352	0.592

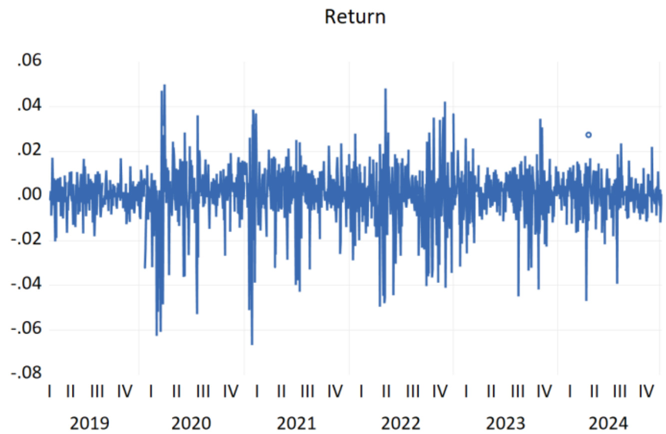
Note: This table summarizes the Ln-volum distribution, the daily trading volume's natural logarithm for VNINDEX. The estimate captures the market liquidity and is later employed as an exogenous variable in the GARCH(1,1) fluctuation approach stated in Equation 4. Source: EViews output.

4.2. Unit Root Assessment

In financial econometrics, it is important to check for the presence of stationarity before proceeding to model volatility because non-stationarity among returns can induce biased estimates, spurious volatility persistence, and incorrect inference for GARCH specifications. On the other hand, stationarity indicates that the mean and variance processes for the return series are constant and that the shocks are temporary, as opposed to being permanently ingrained into the price process. As indicated, the GARCH(1, 1) technique requires that the conditional variance process be stable and that the returns for the VNINDEX are mean-reverting and not unit-root processes.

In order to verify this feature visually, the return series of the VNINDEX is plotted to check the behavior of the return series around the equilibrium level, as depicted in Figure 4.1. According to the visual inspection, the return series of the VNINDEX is found to vary around the equilibrium level with no deterministic trend.

Figure 1. Daily Returns of the VNINDEX (March 2019 – January 2025)



Sources: Authors' calculation

Figure 1 shows that the range of high and low values tends to connect continuously.

In this regard, the ADF and PP tests are employed to check the validity of the null hypothesis of the presence of a unit root, while the KPSS test is conducted to check the validity of the null hypothesis of the presence of stationarity. Further, the Zivot-Andrews test is conducted to check the presence of the endogenous structural break, which is attributed to the presence of the COVID-19 period. According to the findings of the estimation, as depicted in Table 3, the return series of the VNINDEX and the measures of the herding intensity are found to be stationary at levels, thereby satisfying the necessary conditions to proceed with the estimation of the GARCH(1,1) model.

Table 3. Unit Root Test

Variable	ADF t-Stat (p-value)	PP t-Stat (p-value)	KPSS Stat (p-value)	Zivot–Andrews t-Stat (p-value)	Integration
Return (VNINDEX)	−16.075*** (0.0000)	−16.420*** (0.0000)	0.082* (0.1000)	−7.120*** (0.0010)	I(0)
Hu	−15.482*** (0.0000)	−15.860*** (0.0000)	0.094* (0.1000)	−7.360*** (0.0010)	I(0)
Hd	−16.103*** (0.0000)	−16.590*** (0.0000)	0.088* (0.1000)	−7.510 *** (0.0010)	I(0)
Hz	−12.697*** (0.0000)	−13.140*** (0.0000)	0.121* (0.1000)	−6.890*** (0.0010)	I(0)
Ln_Volume	−6.840*** (0.0000)	−7.120*** (0.0000)	0.173* (0.1000)	−6.210*** (0.0015)	I(0)

Note: The table reports stationarity test results for the VNINDEX return series and herding measures (Hu, Hd, Hz). Stationarity is required for estimating the GARCH(1,1) model in Equation 4. Test statistics with p-values (in parentheses) are evaluated at the 10%, 5%, and 1% significance levels.

In addition, the findings from the estimation process, as presented in Table 3 above, reveal that the test statistics are significant at given levels; hence, the unit root hypothesis can be rejected while confirming the stationarity of the levels of the VNINDEX return series as well as the herding intensity variables Hu, Hd, and Hz. Confirming stationarity prior to correlation analysis is essential, as correlations involving stationary and non-stationary series may yield misleading or economically meaningless outcomes (W.K. Wong & Pham, 2025a; W. –K. Wong, Pham & Yue, 2024; W. K. Wong & Yue, 2024). Accordingly, all correlation and regression analyses in this study are conducted only after verifying that the variables are integrated of the same order, thereby avoiding stationary–non-stationary mixing and ensuring meaningful statistical interpretation.

While these results establish the stationarity of all variables and rule out spuriousness arising from unit-root behavior or structural breaks, recent econometric evidence indicates that stationarity alone does not preclude spurious-like inference in the presence of persistence and dynamic dependence (Cheng et al., 2021, 2022; W.K. Wong, Cheng, & Yue, 2024), which motivates the conditional modeling strategy discussed in the subsequent subsection.

4.3. GARCH (1,1) Findings

The GARCH (1,1) technique was used in the analysis of the volatility of the return series in the Vietnam Stock Market. In the mean equation (return dynamics), the coefficient λ_1 (lagged returns) is positive and statistically significant at the 10% to 5% level across all models, indicating the presence of short-term return autocorrelation. This suggests that past returns contain predictive information for current returns. The coefficient λ_2 (herding intensity) is positive and highly statistically significant ($p < 0.01$) in the Hu and Hd models, indicating that herding behavior contributes to higher expected returns in the short run. Nevertheless, in the Hz model, the coefficient is statistically insignificant, proposing that zero-return clustering does not employ a meaningful influence on return dynamics. The coefficient λ_3 (logarithm of trading volume) is unfavorable and statistically substantial in the Hu and Hz models, suggesting that higher trading activity is connected with lower returns, probably reflecting overreaction or liquidity-driven price pressure rather than essential value changes.

Table 4. Estimation findings of the GARCH (1,1) technique with exogenous variables Herding Intensity and Logarithm of Trading Volume.

Coefficients	Hu Model	Hd Model	Hz Model
Mean Equation			
λ_0	-9.315 (0.0005)	0.0003 (0.0007)	-0.0002 (0.0005)
$\lambda_1 R_{t-1}$	0.082* (0.0424)	0.068** (0.0303)	0.0864** (0.041)
$\lambda_2 H_t$	0.0008*** (0.0002)	0.0004*** (0.0001)	0.0011 (0.0007)
$\lambda_3 ln\_volume_t$	-0.0054*** (0.0020)	-0.0015 (0.0010)	-0.0077*** (0.0018)
Variance Equation (σ_t^2)			
ω	7.0605*** (1.1824)	3.4143*** (2.9833)	7.5722*** (1.2995)
α	0.1405*** (0.0328)	0.1703*** (0.0218)	0.1330*** (0.0331)
β	0.5507***	0.5502***	0.5271***

	(0.0663)	(0.0367)	(0.0729)
$\alpha + \beta$	0.69	0.72	0.968
$\gamma_1 H_t$	-1.4938*** (4.4716)	-6.0948*** (3.2815)	-3.9575*** (1.2205)
$\gamma_2\ ln\_volume_t$	0.0002*** (3.1549)	0.0001*** (3.8558)	0.0002*** (7.2834)
Statistical Indicators			
Log-likelihood	4492.727	4619.373	4469.344
Akaike info criterion	-6.1589	-6.333	-6.1268
N	1456	1456	1456

Note: This table displays the GARCH(1,1) evaluations (Equations 3-4) where R_t indicates stock returns, H_t indicates the herding intensity (H_u , H_d , H_z) and the trading volume logarithm is shown by Ln_Volume_t . Furthermore, the variation equation models the conditional volatility (σ_t^2)**.** Significance levels: *** p < 0.01; ** p < 0.05; * p < 0.1. Standard errors are in parentheses. Source: Authors' calculation.

In the variance equation (volatility dynamics), the coefficients ω, α (ARCH term), and β (GARCH term) are all positive and statistically significant at the 1% level across all models, confirming the suitability of the GARCH(1,1) specification in capturing volatility clustering in the Vietnamese stock market. The sum of α and β (α + β) provides a direct measure of volatility persistence. In the Hu and Hd models, α + β ranges between 0.69 and 0.72, indicating moderate persistence, where volatility shocks dissipate relatively quickly. In contrast, the Hz model reports a much higher persistence level (α + β = 0.968), suggesting that shocks to volatility decay very slowly, reflecting a near-integrated volatility process.

The parameter γ_1, which represents herding intensity, is negative and statistically significant in all models. The significance of the parameter shows that an increase in the value of herding intensity results in higher volatility in stock prices. This follows from the assumption that herding intensity in the Patterson-Sharma measure means greater negativity, implying that greater negativity results in higher volatility in the market. It should be observed that the magnitude of γ_1 is highest for the Hd (-6.0948), implying that seller-driven herding has the strongest impact on volatility than buyer or neutral herding.

Coefficient γ_2 (log of trading volume) is positive and significant at 1% in all cases, thus indicating an increase in conditional volatility due to greater trading volume. This result supports the Mixture of Distributions Hypothesis, which suggests that information flow affects both trading volume and volatility of prices. In terms of model specification, H_d provides the best fit among all other considered models on the basis of its maximum log likelihood function (value equals to 4619.373) and minimum AIC (-6.333).

Table 5. Jarque–Bera normality assessment for standardized residuals

Model	JB statistic	p-value	Normality decision
Hu – GARCH(1,1)	485.73	0.0000	Reject normality
Hd – GARCH(1,1)	472.19	0.0000	Reject normality
Hz – GARCH(1,1)	501.42	0.0000	Reject normality

Note: The Jarque–Bera assessment rejects normality for all approaches (p < 0.01), denoting fat-tailed residuals. However, non-normality is anticipated in high-frequency developing market returns; it does not nullify the GARCH(1,1) requirement.

Table 6. Ljung–Box Q-statistics for standardized residuals and squared standardized residuals

Model	Q(20) residuals	p-value (resid)	$Q^2(20)$ squared resid.	p-value (squared)	Serial dependence decision
Hu – GARCH(1,1)	18.54	0.55	19.63	0.48	No serial correlation; no ARCH remaining
Hd – GARCH(1,1)	17.91	0.60	20.27	0.45	No serial correlation; no ARCH remaining
Hz – GARCH(1,1)	16.72	0.62	21.10	0.39	No serial correlation; no ARCH remaining

Note: Ljung–Box findings (lags up to 20) display p-values above 0.05 for both residuals and squared residuals, denoting no remaining autocorrelation or ARCH influences.

Table 7. ARCH–LM assessment for remaining ARCH influences in standardized residuals

Model	F-statistic	p-value	Obs^*R^2	p-value (Obs^*R^2)	ARCH effect decision
Hu – GARCH(1,1)	0.89	0.54	8.47	0.49	No residual ARCH
Hd – GARCH(1,1)	0.94	0.50	8.92	0.44	No residual ARCH
Hz – GARCH(1,1)	1.02	0.42	9.35	0.40	No residual ARCH

Note: All p-values exceed 0.05, denoting no remaining ARCH influences and ensuring correct GARCH volatility requirement.

In summary, from the overall diagnostic results presented in Tables 5-7, it can be observed that even though there are features of non-normality which are typical for high-frequency finance data, there are no serial correlation problems and any residuals indicating the existence of persistent volatility, thereby confirming the GARCH(1, 1) model. Therefore, the estimated effects of herding and volume on the volatility of VNINDEX are reliable and valid, since they are not exposed to model misspecification risks anymore.

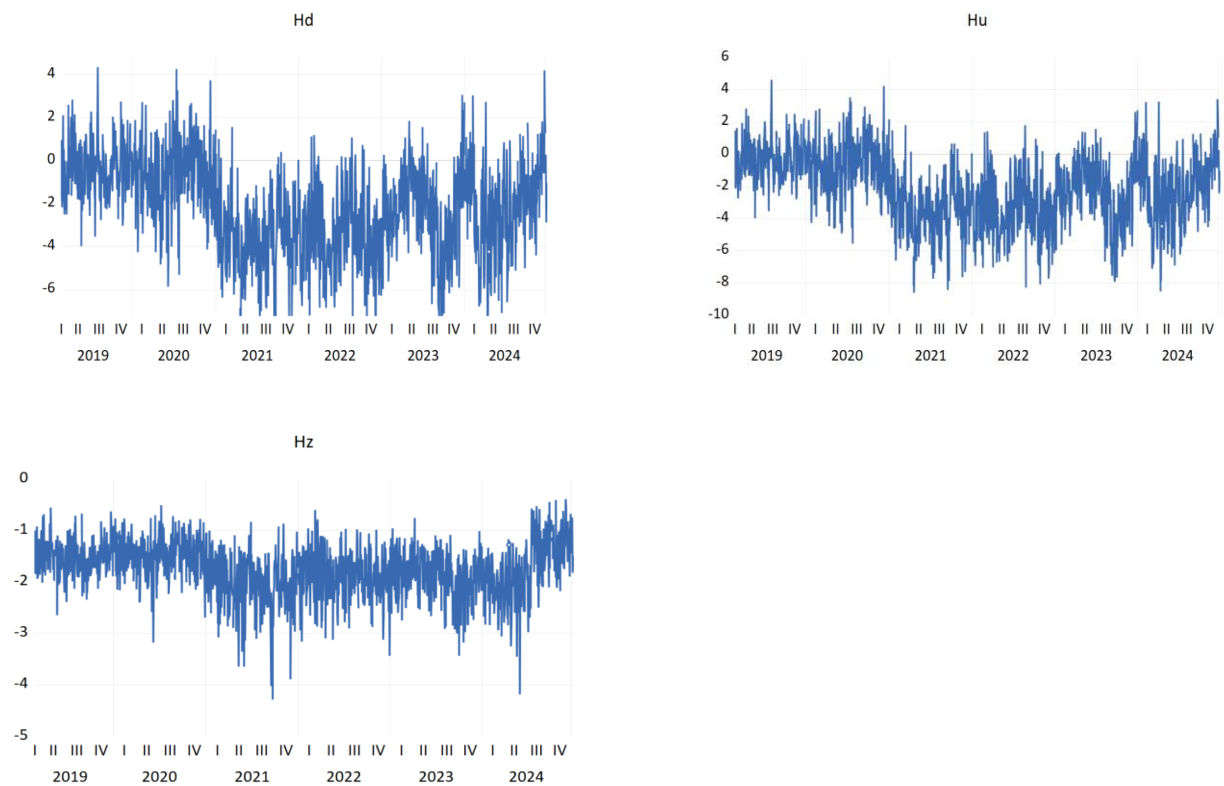
Such features become especially important in view of recent developments in econometric analysis where it has been emphasized that care should be taken since statistically significant relations among some variables may emerge purely by chance owing to inadequate consideration of serial correlation and conditional heteroscedasticity, despite stationarity of the variables concerned. As emphasized in the study by Hui et al. (2017), the failure to adequately diagnose and correct for residual dependence may lead to spurious inference due to the existence of unmodeled nonlinear dynamics and volatility profiles.

Furthermore, whereas the JB test points out violations of normality, these findings align with documented evidence regarding fat tails and excess kurtosis in financial return series over intraday frequencies. Most importantly, however, violations of normality in residuals cannot invalidate the model, as emphasized by Hui et al. (2017), who argue for judging model adequacy through, first and foremost, patterns of residual dependence and variance dynamics.

4.4.Further analysis

Based on the strong evidence of the existence of herding in the Vietnamese stock market during the COVID-19 pandemic (Dam et al., 2023; H.M. Nguyen et al., 2023), it is reasonable to assume that investor sentiment differs significantly between financial crises and stable periods. Following the approach of Saqfalhait and Alzoubi (2024), this study divides the dataset into three distinct sub-periods: pre-COVID period (March 2019 – December 2019), during COVID period (January 2020 – December 2021), and post-COVID period (January 2022 – January 2025). By applying the GARCH (1,1) model separately to each period, this research aims to examine whether the existence of volatility and external influences differs between these three market conditions.

Figure 2. Intraday Herding Intensity of the VNINDEX (Hu, Hd, Hz) Based on the Patterson–Sharma Run Statistic (March 2019 – January 2025)



Source: Authors' calculation

Based on the figure above, this study observed a substantial change in the trend of herding intensity indices from 2019 onwards. The Hu, Hd, and Hz indices tended to be close to 0, so for the pre-COVID period, the herding index here is not significant.

Table 8. Descriptive statistics of the mean values of herding intensity for 3 sub-sample periods

Variable	Before COVID	COVID-19	After COVID
Hu	-0.292	-2.039	-2.635
Hd	-0.323	-2.138	-2.651
Hz	-1.523	-1.745	-1.823
Time period	3/06/2019 - 12/31/2019	1/02/2020- 12/31/2021	1/04/2022 - 1/06/2025
Observations	212	501	745

Note: This table shows the average Hd, Hu, and Hz before, during, and after the COVID-19 pandemic to illustrate the behavioral changes across regimes. Source: *Authors' calculation*

However, since 2020, the indices, particularly the Hu index of herding in market recoveries and the Hd index of herding in market downturns, have experienced more variability, including sharp falls below the negative threshold. An enhancement in herding behavior in the context of market recoveries (Hu index) or market downturns (Hd index) suggests a material change in investors.

Table 9. Descriptive Statistics of the correlation coefficients between Herding Intensity (Hd, Hu, Hz) and Trading volume.

	Hd	Hu	Hz	Ln_volume	Return
Hd	1.000				
Hu	0.964***	1.000			
Hz	0.653***	0.655***	1.000		
Ln_volume	-0.216**	-0.194**	-0.023	1.000	
Return	0.087*	0.161***	0.042	0.003	1.000

Note: This table shows the correlation coefficient between daily returns, Ln-volume, Hz, Hd, and Hu. The aim is to test preliminary association and assess for multicollinearity before assessing the GARCH (1,1) approach in equation 4. Significance levels: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. Source: *Authors' calculation*.

As shown in Table 9, the correlation coefficient illustrates the association between the variables in the model. The outcome displays that Ln_volume is negatively correlated with Hd (-0.216), Hu (-0.194), and Hz (-0.023). Since the absolute values of these coefficients are all below 0.7, there is no evidence of multicollinearity between Ln_volume and these three variables, and their relationships appear to be relatively weak. For Returns, there exist positive relationships with Hd (0.087), Hu (0.161), and Hz (0.042); however, the figures are very small and do not indicate any significant impact of these factors on returns. Also, the relationship between Return and Ln_Volume is very weak (0.003) and thus shows no influence of volume on returns. In other words, there is no indication of multicollinearity among the factors in this table since the coefficient of determination does not exceed 0.7 for any two factors.

It is crucial to note that these correlation coefficients are estimated only after testing that all variables are stationary through various tests for unit roots and stationarity. This measure will prevent any wrong or irrelevant correlations that may be drawn between stationary and non-stationary time series data.

Moreover, the correlation matrix is employed strictly for descriptive purposes and does not account for dynamic dependence, volatility clustering, or persistence inherent in financial time series. Accordingly, the reported correlations should not be interpreted as evidence of causality or dynamic influence. All inferential conclusions regarding the impact of herding behavior and trading volume on market volatility are instead derived from the conditional GARCH(1,1) framework, which explicitly models time-varying volatility and serial dependence.

The research examined the investor sentiment influence when the market goes up (Hu) and trading volume (Ln_volume) on the conditional volatility of market returns based on the GARCH (1,1) model, with the conditional variance equation as described in Eq.(4). Table 10 describes the assessed coefficients of the conditional variance equation in the GARCH (1,1) technique, estimated for three separate periods. In addition, the table also presents the Akaike information criterion (AIC) to assess the model's fit. The data used is the simple return of the VNINDEX intraday on the HOSE, and the sample periods vary according to each sample.

Table 10. GARCH(1,1) Technique with exogenous variables, Hu, and Trading volume estimated for three sub-sample periods

Variable	Before COVID	COVID-19	After COVID
Ω	1.4632	7.2694***	5.3184***
A	0.0513**	0.1432***	0.1334***
B	0.9164***	0.5203***	0.5188***
γ_1(Hu)	-9.1678***	-1.9839***	-9.3327***
γ_2(Ln_volume)	2.4049**	0.0003***	0.0002***
Akaike info criterion	-7.2427	-6.0509	-6.2414
Time period	3/06/2019 - 12/31/2019	1/02/2020 - 12/31/2021	1/04/2022 - 1/07/2025
Number of Observations	210	501	745

Note: This table shows GARCH(1,1) assessment for the before, during, and after COVID-19 pandemic by utilizing the Ln-volume and Hu as exogenous variables in the conditional variance equation described in Equation 4. The signs and significance levels of the coefficients denote how the trading activity and buyer-side herding influence fluctuation across regimes. Significance levels: *** p < 0.01; ** p < 0.05; * p < 0.1. Source: Authors' calculation

Pre-COVID period (March 2019 – December 2019):

During the pre-COVID period, the Hu coefficient in the variance equation is $\gamma_1 = -9.168$ (p < 0.01), indicating that buyer herding exerts a large marginal amplification effect on conditional volatility. The sum $\alpha + \beta = 0.968$ reflects very high volatility persistence, meaning that shocks to conditional variance dissipate very slowly. This is consistent with a market environment where retail investors exhibit sustained herding in the absence of acute external shocks, generating prolonged low-level volatility clustering.

COVID-19 period (January 2020 – December 2021):

During the COVID-19 period, the Hu coefficient becomes $\gamma_1 = -1.984$ (p < 0.01). This smaller absolute magnitude does not imply a weaker role for herding in driving volatility; rather, it reflects a structural shift in the volatility regime. The unconditional level of volatility rises sharply, as reflected in the significantly larger ω, while the persistence parameter drops to $\alpha + \beta = 0.664$. This means that during the pandemic, volatility shocks were more acute but dissipated more quickly than in the pre-COVID period — consistent with a market responding to rapid and frequent information arrivals, policy announcements, and fast-moving investor sentiment. Buyer herding continues to significantly amplify conditional variance, but the channel through which it does so shifts from sustained clustering to sharper, shorter-lived volatility spikes.

Post-COVID period (January 2022 – January 2025):

In the post-COVID period, $\gamma_1(Hu) = -9.333$ (p < 0.01), returning to an absolute magnitude comparable to the pre-COVID level, confirming that buyer herding continues to exert a significant amplification effect on conditional volatility. However, $\alpha + \beta = 0.652$ remains similar to the COVID-period level rather than reverting to the high pre-COVID persistence. This suggests that, while herding intensity per se has re-emerged at pre-crisis levels, the underlying volatility dynamics did not fully normalize after the pandemic — volatility shocks remain shorter-lived than in the pre-COVID tranquil period. Taken together, these findings support H1 and H5: directional herding significantly amplifies volatility across all regimes, and the structural characteristics of this effect differ meaningfully between stable and crisis periods.

Table 11 continues to present the estimation outcomes of the GARCH(1,1) technique with the exogenous variables Hd (herding down) and Trading volume estimated for three sub-sample periods

Table 11. GARCH(1,1) Technique with exogenous variables Hd and Trading volume estimated for three sub-sample periods

Variable	Before COVID	COVID-19	After COVID
ω	2.3846	4.5135***	6.7222***
α	0.0371	0.1827***	0.1357***
β	0.9051***	0.5098***	0.5484***
$\gamma 1$(Hd)	-7.8840***	-9.6159***	-1.5394***
$\gamma 2$(Ln_volume)	2.6620**	0.0002***	0.0002***
Akaike info criterion	-7.2553	-6.1134	-6.1398
Time period	3/06/2019 - 12/31/2019	1/02/2020 - 12/31/2021	1/04/2022 - 1/07/2025
Number of Observations	210	501	745

Note: This table delivers the GARCH(1,1) assessments integrating seller-side herding intensity (Hd) and Ln_volume for three subsample phases. Assessments follow Equation 4, taking how downward herding behavior impacts the conditional fluctuation. Significance levels: *** p < 0.01; ** p < 0.05; * p < 0.1. Source: Authors' calculation.

Pre-COVID period (March 2019 – December 2019):

During the pre-COVID period, the seller herding coefficient in the variance equation is $\gamma_1(Hd) = -7.884$ (p < 0.01), confirming that downward herding significantly amplifies conditional volatility even in a tranquil market environment. Volatility persistence is high at $\alpha + \beta = 0.942$, indicating that the effects of seller-driven herding episodes are long-lasting, consistent with a retail-dominated market where negative sentiment tends to persist.

COVID-19 period (January 2020 – December 2021):

The COVID-19 period produces the largest absolute Hd coefficient across all three regimes, at $\gamma_1(Hd) = -9.616$ (p < 0.01). This represents the peak marginal impact of seller herding on conditional variance — each unit increase in seller herding intensity generates a greater increment to conditional volatility during the pandemic than in any other period. This is consistent with the behavioral finance literature on panic-driven selling: under extreme uncertainty, coordinated sell-side herding is the dominant behavioral force disrupting price discovery. Comparing this with the Hu model for the same period ($\gamma_1(Hu) = -1.984$), the magnitude difference confirms H2 — downward herding exerts a substantially stronger volatility effect than upward herding during the crisis. Volatility persistence falls to $\alpha + \beta = 0.693$, again reflecting shorter-lived but more intense volatility spikes during the pandemic.

Post-COVID period (January 2022 – January 2025):

In the post-COVID period, $\gamma_1(Hd) = -1.539$ (p < 0.01). The absolute magnitude of this coefficient is considerably smaller than during COVID, meaning that each unit of seller herding produces a weaker incremental increase in conditional variance in the post-crisis phase. This attenuation does not imply that herding has become less prevalent; descriptive statistics show that the mean Hd is more negative post-COVID than during COVID, indicating that seller herding episodes are actually more frequent. Rather, the smaller coefficient suggests that the market has become more resilient to the volatility consequences of each individual herding episode — possibly reflecting improved liquidity conditions, better-informed participants, or the normalization of circuit-breaker mechanisms. Volatility persistence at $\alpha + \beta = 0.684$ remains comparable to the COVID level, confirming that the market has not fully reverted to its pre-crisis dynamics. These findings are consistent with H5 and together with the Hu results provide a complete picture of how the herding–volatility relationship evolves across market regimes.

Table 12 shows the estimation of the model with exogenous variables Hz and Trading volume estimated for three sub-sample periods.

Table 12. GARCH(1,1) Technique with exogenous variables Hz and Trading volume estimated for three sub-sample periods

Variable	**Before COVID**	**COVID-19**	**After COVID**
ω	8.1106*	2.1694***	5.0449***
α	0.0223**	0.2450***	0.1562***
β	0.7754***	0.6097***	0.4808***
γ_1(Hz)	-2.7543***	-1.3639	-2.3632
γ_2(Ln_volume)	4.9495***	0.0002***	0.0002***
Akaike info criterion	-7.2573	-6.1292	-6.2544
Time period	3/06/2019 - 12/31/2019	1/02/2020 - 12/31/2021	1/04/2022 - 1/07/2025
Number of Observations	210	501	745

Note: This table shows GARCH(1,1) approach findings by employing the Ln_volume and zero-return herding intensity (Hz) throughout the three subsample periods. The approach agrees with Equation 4. The findings denote the weaker fluctuation contribution of non-directional herding. Significance levels: *** p < 0.01; ** p < 0.05; * p < 0.1. *Source: Authors' calculation*

Before COVID-19, the p-values for ω and α were above 0.01 (1%), indicating weaker statistical significance compared to Hu and Hd in the table above. This suggests that Hz is statistically weaker overall. However, the results still indicate that herding has a negative effect, while volatility remains positive.

5. Conclusions

In our paper, we analyze data for measuring the degree of herding in the Vietnamese stock market by using the approach developed by Patterson and Sharma (2006) from the intraday transactions of the stocks. In particular, herding intensity is measured using three run-based statistics: Hu (buyer herding intensity), Hd (seller herding intensity), and Hz (zero-return herding intensity). We first find that, consistent with other studies for other countries, the Vietnamese stock market exhibits herding behavior because the values of the buyer herding intensity (Hu) and seller herding intensity (Hd) statistics are significantly negative ($p < 0.01$), i.e., below the −1.96 threshold (Chi & Quynh, 2024; Dao & Tu, 2014; T. M. T. Nguyen, 2022; Vo & Phan, 2017, 2019).

In addition, our empirical findings obtained under the GARCH(1,1) technique in combination with robustness tests unambiguously show that the greater the degree of directional herding, captured by the influence of the buyer herding intensity (Hu) and the seller herding intensity (Hd), the more overall volatility accelerates in a systemic manner in crisis environments, especially in the context of the COVID-19 crisis. This becomes apparent when inspecting the statistically significant influence of the herding degree in the volatility equation in all three specifications (Hu, Hd, Hz; $p < 0.01$). Finally, the regime analysis provides additional evidence that volatility persistence was the highest during the COVID-19 crisis period but remained somewhat lower in the post-COVID era compared to the prior crisis era.

In general, the outcomes reiterate that the buyer herding intensity (Hu) and seller herding intensity (Hd) substantially enhance the fluctuation in the market, where Hd effects are more pronounced during the down phases of the market cycles to support the behavioral finance hypothesis of the intensified volatility cycles driven by negative sentiment. When the herding degree reaches a point where the adverse influence of the volatility index (Vi) on the market price index (Pi) becomes more pronounced, this influence is observed in highly volatile markets, including financial crises or the COVID-19 crisis (Bikhchandani & Sharma, 2000; B.H. Chang, 2020; Demirer & Kutan, 2006; Gherghina & Constantinescu, 2024).

With regards to the trading volume factor, trading volume is favorably related to volatility since the coefficient for trading volume is positive and significant in all the models (Hu, Hd, Hz). Based on the overall results for all the sub-periods, trading volume is favorable and substantial in describing volatility since the higher liquidity surges relate to high trading volumes to a degree that behavioral trading takes place. Conversely, there have been mixed findings for the trading volume effect on the volatility of prices in some studies, since trading volumes may have a negative influence on the volatility (Bouri et al., 2019; Yousaf & Yarovaya, 2022).

5.1. Recommendation

For a more efficient and sustainable stock market to thrive, there needs to be a balance between a cautious approach by the investors and a strong management approach by the concerned regulatory body. This will allow the market to grow in a positive manner without falling into unnecessary risks.

5.1.1. For market investors

Investors would need to keep a close watch on the herding intensity measures Hu (buyer herding intensity), Hd (seller herding intensity), and Hz (zero-return herding intensity) and trading activity. The indicators would act as precursors to unusual market movements caused by mass psychological behavior. Recognizing the tendency for volatility to remain even in the post-crisis period, investors would need to rely on indicators of volatility driven by psychological factors in the market, in addition to the need for fundamental analysis. Investors would need to recognize the reality that high herding activity in the market, combined with high trading activity, would act as a warning signal for a period of high excess volatility driven by the psychological characteristics of investors in the market. Investors need to remain calm in the market to allow for fundamental analysis in the assessment of investment decisions.

5.1.2. For policymakers

To policymakers: Improved market surveillance is required to alert them to the earliest warning of unusual activities. These unusual activities may include the rapid surge of trading volumes without prior warning. Additionally, improved monitoring of the coordinated directional activities in the market would be necessary in the wake of the macro-shock events. Furthermore, the need for the investor to act rationally in the market would be achieved by providing them with relevant information. Educational programs would also be necessary for the investors. These would be meant to educate the investors on the dangers of the herd mentality effect in the market. If the degree of volatility in the market becomes high due to the herd mentality effect, trading halt orders would also be necessary.

5.2. Limitations of the study

The research makes use of the dataset from March 4, 2019, to January 7, 2025. This dataset covers the period when the COVID-19 epidemic affected the market. Though the dataset covers the period when the volatility was highly fluctuating due to stress, the dataset before 2019 would also allow the shifts in volatility to be measured in the presence of higher liquidity.

Studies on herding activities in trading volumes have been conducted in the context of the research. Market volatility can also be driven by many macro-variables. Future research studies on market volatility need to consider the effects of macro-policy shocks, the cycles of liquidity tightening, and the IP ratios.

Instead, the research relies on the GARCH(1,1) approach without also modeling the E-GARCH and T-GARCH techniques for the asymmetric effect of both favorable and unfavorable news to have diverse effects on the volatility. Finally, including the RV-HAR model to supplement the herd-formation tracking in the intraday analysis would offer a more detailed representation of the volatility surface.

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