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Overconfidence Behavior and Dynamic Market Volatility: Empirical Evidence from the Vietnamese Stock Market

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ABSTRACT

This study examines the relationship between investor overconfidence and dynamic market volatility in the Vietnamese stock market, a frontier market distinguished by rapid growth and the dominance of individual investors. Although the overconfidence–volatility framework has been tested across many developed and emerging markets, Vietnam has remained largely unexamined despite exhibiting the speculative boom-and-crash cycles and heavy retail participation that make it a compelling case for behavioral analysis. Drawing on the frameworks of Chuang and Lee (2006) and Jlassi et al. (2014), we analyze daily VN-Index price and trading-volume data from the Ho Chi Minh Stock Exchange (HOSE) over 2016–2025, comprising 2,497 observations. Log trading volume is decomposed via OLS regression on five lagged daily returns into an overconfidence-driven (overreaction) component and a non-overconfidence component, which are then incorporated into an EGARCH(1,1) model to assess their contributions to conditional volatility. The results support all three hypotheses. The overconfidence component has a positive and highly significant effect on conditional volatility ($f_3 = 0.136$, $p < 0.01$) that substantially exceeds that of the non-overconfidence component ($f_4 = 0.004$), indicating that behavioral trading is a primary driver of market instability. Volatility is highly persistent ($f_2 = 0.950$) and asymmetric, with negative shocks generating larger responses than positive shocks of equal magnitude ($K = -0.153$, $p < 0.01$). These findings extend the international overconfidence-volatility literature to an emerging market and highlight the role of investor psychology in shaping market risk.

Keywords: Overconfidence, Market volatility

1. Introduction

One way to see the nature of the social oscillator at work in behavioral finance is to regard stock market volatility as influenced by not only fundamental market data but also psychological biases that investors employ while forming impressions about market movement. In an environment of uncertainty, investors are prone to make decisions shaped by such biases and not by logical reasoning. Overconfidence may lead them to underestimate market risk when whatever confidential input about fundamentals they do have. Four forms of market strategies are identified in the following text below.

Traders who believe their abilities exceed their actual market knowledge can increase market volatility because their trading behavior becomes excessive. Investors who achieve positive returns believe their success originates from their own skills rather than market conditions or random chance. Their growing confidence leads them to increase their trading activities. When many investors exhibit this behavior, it can generate abnormally high trading volume, cause prices to deviate from their fundamental value, and contribute to the formation of speculative bubbles. Market sentiment changes, which provoke sudden price swings and give rise to the issue of continuing market instability of these bubbles.

As the scene in the market changes at a rapid pace, price swings occur and the perpetuation of bubble formation brings market instability. All these events are typical of the asymmetric nature of the market where any bad news can cause more market havoc than the positive impacts generated by the optimistic news, particularly when investors are against the good performance. Thecumulative evidence from the study by Jlassi and co-researchers provides compelling support for this view, showing that overconfidence is the main driver of volatility in-volatility-performance, and it emerges as dynamic, clustering, and asymmetric volts on global financial markets. The hypothesis points towards debating that overconfidence generates mistakes on the individual level that germinates instability for the entire market.

This paper is to study on the relationship between overconfidence on the part of investors and the levels of stock market fluctuation in Vietnam overthe period from 2016 through 2026, depending on available data; the main thrust here is: to determine if investors are more apt to trade after they realize high market returns and if this increase in trading behavior is a representation of overconfidence-motivated activity. On the other hand, determination is made whether the overconfidence-induced contribution to trading volume raises the level of market volatility; the study explores the issue of the occurrence of asymmetric volatility in the Vietnamese stock market whereby negativity shocks lead to greater volatility than positively shocked market activities. These theoretical questions should be addressed within the context of Vietnamese investor psychology, the trading behavior itself, and the ways they interplay in causing greater instability in the stock market.

2. Literature Review

2.1. Overconfidence Theory

In behavioral finance, overconfidence can be identified among the strongest biases discovered so far. The simplest definition of overconfidence states that it is undue confidence in our natural instincts for reasoning and making conclusions (Pompian, 2006, p. 41). When investors suffer from overconfidence, they tend to overestimate both their forecasting ability and the accuracy of their information, which causes incorrect probabilities. As Pompian (2006) points out, people tend to think that they know more than they actually do, and their expectations of something definitely happening rarely reach one hundred percent probability. Ackert and Deaves (2010) note that there are four different ways that overconfidence is demonstrated, and its influence on financial decisions is through the direct impact it has on financial decisions. The first instance of overconfidence is where the investor creates a confidence interval that he believes will have market forecasts accurately for his investors, but the range of the forecast fails to meet the market development. It is difficult for the investor to know the real market knowledge since he has created a narrow confidence interval.

The trading behavior of the investors has considerable impact because of these behavioral manifestations. According to Pompian (2006), the following are the four behavioral manifestations that result due to overconfidence: overconfident investors ignore negative signals related to their investments; trade frequently because of their belief that they have better information; ignore risks; and have underdiversified investment portfolios without even realizing that they have taken morerisk than they can afford.The individual investor executes trading activities which lead to unusual spikes in market activity.

The relationship is shown through a straightforward demand model which Ackert and Deaves (2010) developed for theoretical analysis. An overconfident investor places disproportionate weight on their own prior value estimate relative to market price signals. The model shows that higher overconfidence levels which the parameter a_i represents lead to investors showing less interest in particular stocks because they will act more forcefully when they identify price-value discrepancies. The model proves that increasing overconfidence levels in investors results in both higher trading volumes and greater price fluctuations. The theoretical framework predicts that increasing investor overconfidence will create higher trading volumes and price volatility which matches the empirical results of Odean's model (Ackert and Deaves 2010).

ISSN: 2455-8834

Volume:11, Issue:08 "August 2026"

2.2. Self-Attribution Bias

Self-attribution bias is a cognitive tendency that reinforces and perpetuates overconfidence over time by distorting the way investors learn from their own performance outcomes. In particular, the self-attribution bias refers to the tendency of an investor to ascribe success to his or her own abilities, skills, and expertise but failure to circumstances beyond one's control, including "market noise, luck, and other participants' behavior" (Ackert and Deaves, 2010). The asymmetric attribution of causes undermines the rational Bayesian updating of self-conceptions by investors.

Baddeley (2013) frames this dynamic within attribution theory, noting that Hong and Stein (1999) draw on the concept to explain market overreactions: people tend to ascribe success to their own talents and ability, but will attribute adverse events to noise and sabotage. As Ackert and Deaves (2010) explain, when things go well, the overconfident investor attributes the success to great ability, skill, or knowledge far more than an objective consideration of circumstances would warrant, resulting in an increase in overconfidence. Adverse outcomes, on the other hand, are only moderately attributed to personal factors and therefore do not produce symmetrical downward revisions. The practical result, as captured by Gervais and Odean (2001), is that people effectively learn to be overconfident.

In the context of financial markets, the investment cycle is particularly fertile ground for selfattribution bias. Ackert and Deaves (2010) provide a detailed explanation for the process: in rising markets, most securities in the investor's portfolio will generate profits, thereby enhancing the impression of the investor's ability. In the event that prices fall, investors tend to explain the fall by citing factors affecting the entire market or economy, instead of pointing out the mistakes they made in picking the securities. Such a ratchet effect, over time, will serve to amplify confidence levels instead of reducing them.

Moreover, according to Baddeley (2013), self-attribution bias and hindsight bias work together to contribute to overconfidence. Investors who have just witnessed the occurrence of an event assume that they knew all along what would happen, thereby reinforcing their belief that they possess good forecasting skills, which makes them engage in more speculative behavior in future instances.

2.3. Dynamic Overconfidence Framework

Whereas early studies of overconfidence assume the behavior to be an immutable individual attribute, the Dynamic Overconfidence Theory acknowledges the fact that the degree and extent of overconfidence can vary and is determined by the changing dynamics of the marketplace, performance, and demographics. This approach is essential in comprehending why trading

ISSN: 2455-8834

Volume:11, Issue:08 "August 2026"

volumes change within the marketplace and why some investor groups are more overconfident than others. As per Ackert & Deaves (2010), the multi-period theory presented by Gervais and Odean suggests that previous successes increase overconfidence due to self-attribution bias, whereas previous losses have always been downplayed by the individual. According to this model, investors who are experiencing success in the market would have higher levels of overconfidence as compared to new entrants into the market during a specific time period. As a result, a procyclical relationship can be observed, as rising markets create successful investors who are overconfident and contribute to the rise in volumes and prices.

Empirical evidence on the dynamics of overconfidence is notable. Research on German market practitioners reviewed in Ackert and Deaves (2010) found that market experience actually worsened overconfidence, rather than correcting it, which is consistent with the learning-to-beoverconfident view. Those surviving and advancing in financial markets often do so partly because of a run of good fortune, which self-attribution bias leads them to attribute to skill. The same studyfound evidence that overconfidence can increase at the level of the entire market, with past market returns positively correlated with subsequent increases in overconfidence across the investor population, as captured through lagged correlations with trading activity.

The demographic aspect of dynamic overconfidence is no less significant. As revealed in Pompian (2006) and Ackert & Deaves (2010), the landmark study conducted by Barber & Odean discovered that males traded 45% more than females did, resulting in higher transaction costs and lower net returns by about 0.94 percentage points per year compared to those of women. Males who were unmarried traded 67% more than unmarried females, with their net gains falling behind female gains by 1.44 percentage points. This difference was due to overconfidence on the part of males.

2.4. Overconfidence on trading volume and Market Volatility

Overconfidence is a basic behavioral bias that people manifest in the financial market context. This bias results in the assumption that the investors are well aware of the information they know as well as of their skills at investing when, actually, they ignore the risk connected to their investments. The most immediate and overt effect of such behavior is overtrading, according to Shiller (as cited in Jlassi et al., 2014).

Based on the model introduced by Odean (1998), Jlassi et al. (2014) argued that when people trade excessively using noise signals, they create higher expected trading volumes, but lower investment efficiency than passive portfolios. Moreover, as pointed out by Gervais and Odean (2001, cited in Jlassi et al., 2014), overconfidence is a dynamic phenomenon whereby an investor develops a certain level of confidence after experiencing a self-attribution process. People

ISSN: 2455-8834

Volume:11, Issue:08 "August 2026"

usually attribute gains to themselves and any losses to outside sources. The self-attribution process produces a feedback effect where more profitable gains raise confidence levels, thus creating a greater volume of trades for the future periods (cited in Jlassi et al., 2014).

However, the consequences of this psychology do not stop overtrading. While the efficient market hypothesis suggests that prices only fluctuate in response to fundamental news, behavioral finance models assert that overconfidence creates excessive volatility through a mechanism of overreacting to individual information and underreacting to public news (Daniel, Hirshleifer, & Subrahmanyam, 1998). Consequently, short-term bullish and long-term reversal patterns emerge, contributing to overall market instability (De Grauwe, 2012, discussed in Jlassi et al., 2014).

In line with Chuang and Lee (2006) model, Jlassi et al. (2014) noted the ability to separate the trading volumes into an over confidence part (OVER) and a non-over part (NONOVER).

Consequently, overconfidence can be measured directly to examine its effect on market volatility. Based on the analytical tools used, which are the EGARCH, the authors established that the contribution of OVER to conditional variance was greater than the contributions made by all other variables apart from overconfidence. Internationally, Jlassi, Naoui and Mansour (2014) found out that the overconfidence levels were generally higher in developed countries compared to emerging economies. In times of crisis, overconfidence remained prevalent among investors in developed nations because of what Langer (1975) termed as the "illusion of control" as reported by Jlassi et al. (2014). On the contrary, according to Jlassi et al. (2014) citing Moore & Healy (2008) research, there are some emerging Asian markets where investor overconfidence can change to extreme pessimism in case of surprises in the economic environment. Thus, overconfidence is not just a static variable. It is a dynamic phenomenon, and one that can exacerbate external shock leading to long-term economic instability (see Akerlof & Shiller, 2009; Jlassi et al).

2.5. Asymmetric volatility

The asymmetry in volatility, often referred to as the "leverage effect," is prevalent in the stock markets and entails that the reaction of volatility is more sensitive to negative returns shocks (or bad news) than positive returns shocks (or good news). There are three explanations of this effect: financial leverage effect (when the value of assets falls, the debt/equity ratio increases), feedback effect on volatility expectations (when investors expect higher levels of future volatility, the required rate of return will be increased, resulting in price decline), and finally, the psychology of investors, which is a topic of interest in behavioral finance.

ISSN: 2455-8834

Volume:11, Issue:08 "August 2026"

The EGARCH model (Nelson, 1991) is used as the benchmark for measuring asymmetry using its K coefficient. The coefficient K is statistically significant at the negative end, thus indicating that negative shocks generate larger conditional volatility effects compared to positive shocks. In their empirical investigation, Jlassi et al. (2014) found evidence of asymmetric volatility with a positive and statistically significant Asymmetric Degree Index (AD) in 27 countries. It should be pointed out that this characteristic is observed not only during crises but also in normal times.

Overconfidence is vital in explaining asymmetric volatility. In times of bull market, overconfident traders will have an aggressive trading style, thus driving the prices above their actual worth while at the same time undervaluing the likelihood of any possible catastrophic occurrence. This makes the asymmetric effect (parameter K) even more pronounced during the tranquil period than in terms of the overall average. In case the trend reverses, the sudden realization of overvalued securities, coupled with the necessity for selling leveraged securities, causes a deep plunge and an increase in volatility. The quantitative study reveals that the overconfidence variable (OVER) is stronger in predicting conditional volatility than other non-psychological variables (NONOVER).

Overconfidence is thus the major factor responsible for market instabilities. In cases of emerging economies such as Vietnam, which are characterized by large information asymmetry, individual dominance, and behavioral factors such as crowd psychology and panic, the asymmetric effect gets significantly magnified.

2.6. Hypothesis development

Over volatility due to overconfidence bias is highly significant and consistent in the case of developed markets. The initial studies performed in the US capital market have shown that the trading volume goes up after high-return periods, with overconfidence being a major component of conditional variance (Chuang & Lee, 2006, cited in Jlassi et al., 2014). In addition, in most advanced countries, the impact coefficient of overconfidence (f3) was highly positive (Jlassi et al., 2014). It should be stressed that the overconfidence bias did not vanish during the Subprime Crisis in the US and was firmly entrenched in investor attitudes. It is a clear illustration of the "illusion of control syndrome" when investors believe that they can control the market regardless of the economic situation (Langer, 1975; Abbes, 2012, cited in Jlassi et al., 2014).

Hypothesis 1: Trading volume driven by overconfidence has a positive and significant impact on conditional market volatility ($f_3 > 0$)

On the other hand, the evidence found through studies conducted in developing markets seems tobe much more scattered and complicated. While individual investors who account for most of the activity in the markets of developing countries show high levels of overconfidence than do

ISSN: 2455-8834

Volume:11, Issue:08 "August 2026"

institutional investors, there is a complex "dynamic" aspect to this attitude which emerges when the survey sample size is increased to 27 countries. Some markets in Asia like those in Hong Kong, India, and the Philippines were found to have shown very high levels of overconfidence during tranquil times resulting in over-speculation. On the other hand, markets in China, South Korea, Taiwan, and Thailand showed pessimism or underconfidence due to negative impact coefficients (Jlassi et al., 2014).

Hypothesis 2: The overconfidence effect to the conditional volatility should greater than the other factors combine ($f_3 > f_4$).

The dynamic nature of sentiment is further emphasized when a market experiences a crisis. Unlike the firm commitment to belief exhibited by investors in developed economies, emerging markets' investors have been noted by Abbes (2012) and Jlassi et al. (2014) to suffer a sudden shift in psychology, transitioning from an extremely optimistic outlook on the future to extreme negativity.

With market realities constantly going against their beliefs, investors find themselves at a loss when faced with the realization of their constant wrongdoings, resulting in panic, reduced transaction volumes, and lack of confidence (Moore & Healy, 2008). The combination of information disparity, illiquidity, and dominance of individual investors in such markets enhances this behavioral tendency (Chuang & Wang, 2005; Chen et al., 2007)

Hypothesis 3: Bad news affects volatility more strongly than good news ($K < 0$).

3. Data analysis

3.1. Data collection

The study examines data on price and volume traded on a daily basis for VN-Index on Ho Chi MinhStock Exchange (HOSE) in Vietnam. The sample period considered in this study spans from 2016 through 2025 with the exclusion of non-business days and public holidays. This leaves a total number of 2497 observations on business days. Each business day comprises data on opening, closing prices and trading volume.

Daily returns are calculated using continuous compounding: $Rt = \ln(Close_t/Close_{t-1})$, where t indicates the price at which trading closes. This method is the preferred option when it comes to estimating daily returns as it guarantees the normality of returns over time (Campbell, Lo, and MacKinlay, 1997).

ISSN: 2455-8834

Volume:11, Issue:08 "August 2026"

Table 1: Variable description

Variable	*Notation*	*Definition*
Return	R_t	*Daily log return: ln(Closet / Closet-1)*
Log Volume	LV_t	*Natural log of daily trading volume*
Lagged Return k	R_{t-k} *(k = 1 - 5)*	*Return lagged by k trading days*
Overreaction (OVER)	$OVER_t$	*Fitted value of log volume attributable to past returns*
Non-Overreaction (NONOVER)	$NONOVER_t$	*Residual component of log volume not explained by past returns*

The trading volume is converted into natural logarithm (Log Volume - LV_t) to remove the skewness of volume (volume skewness = 2.155) and achieve homoskedasticity. Five lagged return series (R_{t-1}, R_{t-2}, R_{t-3}, R_{t-4} and R_{t-5}) have been constructed by taking the one day lagged returns consecutively.

3.2. Methodology

The study adopts the trading volume decomposition framework to distinguish between the overreaction and non-overreaction components of market activity. This approach follows the notion that abnormal trading volume may be driven by behavioral biases, particularly investor overreaction to past return signals. By regressing log volume on a sequence of lagged returns, we isolate the fraction of volume that is mechanically explained by past price movements — interpreted as the overreaction component — from the remainder that reflects other market dynamics.

3.2.1. Lag Length Selection

To determine the appropriate number of lagged return terms, we estimate four candidate OLS regression models (through), each incorporating lags from 1 to 5 days:

$$LV_t = \alpha + \beta 1 R_{t-1} + \beta 2 R_{t-2} + \ldots + \beta k R_{t-k} + \varepsilon t \ (k = 2, 3, 4, 5)$$

For this particular model, we employ natural logs of trading volume and market return, which is lagged by k days. In selecting an appropriate model, two different criteria, namely the Akaike Information Criterion (AIC) and Schwarz Criteria (SC), have been used in this study. Both are designed to reward simplicity but penalize complexity at the same time.

ISSN: 2455-8834

Volume:11, Issue:08 "August 2026"

Table 2: Lag length selection criteria

Model	*Lag Length*	*AIC*	*SC*
eq2	*2*	*4.8848*	*4.8873*
eq3	*3*	*4.8832*	*4.8925*
eq4	*4*	*4.8818*	*4.8935*
eq5	*5*	*4.8806*	*4.8857*

The AIC for the model with five lagged values is the smallest (4.8806), suggesting that it has the best goodness of fit after accounting for its complexity. Even though the SC attains its minimum with five lagged values as well, the improvement in the SC from the fifth lag is an indication of true information.

3.2.2. Estimation of the Selected Model

The selected regression model is:

$$LVt = 17.558 + 11.029Rt\text{-}1 + 11.254Rt\text{-}2 + 11.469Rt\text{-}3+11.212Rt\text{-}4 + 11.374Rt\text{-}5 + \varepsilon t$$

All lagged return coefficients are positive and quite consistent with one another at between 11.21 and 11.47. In essence, whether the market rises or falls, there is an increase in the volume of trade in the five days after the event. Essentially, all market events, irrespective of their nature, prompt investors to take action by making purchases or sales in response to the performance of the market. The finding is consistent with the overreaction hypothesis, which suggests that market events tend to trigger an outbreak of excessive trading activity. The intercept of 17.558, on the other hand, represents the volume of trade that occurs independently of the market's past performance.

Table 3: Coefficient estimates of selected model (eq5)

Parameter	*Variable*	*Estimated Coefficient*
α (Constant)	*Intercept*	*17.5582*
β1	*Rt-1 (Lag 1)*	*11.0291*
β2	*Rt-2 (Lag 2)*	*11.2540*
β3	*Rt-3 (Lag 3)*	*11.4688*
β4	*Rt-4 (Lag 4)*	*11.2121*
β5	*Rt-5 (Lag 5)*	*11.3743*

3.2.3. Volume Decomposition

Based on the coefficient estimates, the total log trading volume can be expressed as a combination of two separate terms that sum together:

ISSN: 2455-8834

Volume:11, Issue:08 "August 2026"

$LVt = OVER_t + NONOVER_t$

The OVER term reflects the portion of trading volume attributable to changes in prices for the previous five days:

$OVERt = 11.029R_{t-1} + 11.254R_{t-2} + 11.469R_{t-3} + 11.212R_{t-4} + 11.374R_{t-5}$

The (NONOVER) represents the residual trading activity that cannot be attributed to investors' responses to recent returns:

$NONOVERt = LVt - OVERt = 17.559 + \varepsilon t$

This split is based on a simple idea: the part of trading volume driven by overreaction to price signals reflects short-term, emotion-driven behavior, while the non-overreaction part picks up things like informed trading, liquidity needs, and other structural factors. The residual term (εt) soaks up any day-specific variation in volume that past returns can't explain, so NONOVER still captures the variation around the baseline of 17.558. As a sanity check, adding OVERt and NONOVERt back together should perfectly recover the original log volume series — and it does,with the difference coming out to exactly zero for every single observation. This confirms that the decomposition is internally consistent.

3.3. Results

3.3.1. EGARCH Estimation Results

To examine whether overconfidence-driven trading activity contributes to conditional market volatility, the decomposed volume components are incorporated into an EGARCH (1,1) specification. The estimated variance equation is written as:

$$lnh_t = \omega + f_1\left[\frac{|\eta_{t-1}| + K\eta_{t-1}}{\sqrt{\eta_{t-1}}}\right] + f_2 lnh_{t-2} + f_3 OVER_t + f_4 NONOVER_t$$

where ht denotes conditional variance, $f1$ measures the effect of recent shocks on volatility, K captures the asymmetric response of volatility to good and bad news, $f2$ measures volatility persistence, $f3$ represents the overconfidence effect, and $f4$ represents the effect of nonoverconfidence-related trading volume.

ISSN: 2455-8834

Volume:11, Issue:08 "August 2026"

Table 4: EGARCH (1,1) Estimation Results for VN-Index

Parameter	*Interpretation*	*Coefficient*	*p-value*
ω	*Constant*	*-0.694745*	*0.0000*
$f1$	*Shock effect*	*0.232251*	*0.0000*
K	*Asymmetric effect*	*-0.153023*	*0.0000*
$f2$	*Volatility persistence*	*0.949851*	*0.0000*
$f3$	*OVER effect*	*0.136192*	*0.0000*
$f4$	*NONOVER effect*	*0.003594*	*0.0000*

The EGARCH results provide strong evidence that volatility in the Vietnamese stock market is influenced by both behavioral and structural factors. First, the shock effect coefficient $f1$ = 0.232251 is positive and highly significant, indicating that recent innovations increase conditionalvolatility. This implies that new market information, whether positive or negative, has an immediate effect on market risk.

Secondly, the persistence coefficient of $f2$ = 0.949851 is positive and highly significant, being extremely close to one. This means that the stock market of Vietnam shows strong clustering or persistence in volatility, which means that the increased volatility persists over an extended period of time rather than reverting back to its long-term level very quickly.

Third, the asymmetry coefficient of K = -0.153023 is negative and highly significant at the 1% level. This verifies the existence of asymmetric volatility in the stock market of Vietnam because of which the negative shocks play a more significant role in increasing the conditional volatility as compared to positive shocks of the same size.

Most importantly, the coefficient on the overconfidence-related component of trading volume is positive and statistically significant ($f3=0.136192$, $p<0.01$). This result indicates that the component of trading volume associated with investor overconfidence contributes positively to market volatility. Thus, higher levels of overconfidence-driven trading are associated with stronger fluctuations in the VN-Index. By contrast, the coefficient on the non-overconfidence component is also positive and significant ($f4=0.003594$, $p<0.01$), but its magnitude is substantially smaller than that of the OVER coefficient.

This implies that although other non-behavioral or non-overconfidence-related factors also affect volatility, their contribution is much weaker than the contribution of overconfidence.

ISSN: 2455-8834

Volume:11, Issue:08 "August 2026"

Hypothesis 1: Trading volume caused by overconfidence has a positive and statistically significant influence on conditional volatility in the market (f3 > 0).

This hypothesis is valid. The coefficient of OVER is positive (0.136192) and significantly differs from zero at the 1% level of significance. Hence, the overconfidence-induced trading activities have an impact on the volatility in Vietnam.

Hypothesis 2: The effect of overconfidence on conditional volatility exceeds the effect of all other factors except overconfidence (f3 > f4).

This hypothesis is also true because the coefficient of OVER (0.136192) is considerably larger than the coefficient of NONOVER (0.003594). Thus, the behavioral trading volume factor has more influence on the volatility than the other factor.

Hypothesis 3: Negative returns result in greater conditional volatility than positive returns of the same amount (K<0).

The result above is also true. The asymmetry parameter is significantly negative (K=-0.153023, p<0.01), which shows that “bad news” has a bigger impact on market volatility than “good news.”

5. Conclusion

These results confirm the behavioral finance claim about excessive investor confidence as a potential source of market-wide instabilities. In the Vietnamese case, the plausibility of this statement is higher since this market consists mainly of individual investors, whose trading is highly dependent on sentiments, gains, and speculation. Positive returns will create an impression of successful forecasting on the part of investors and lead to an increase in trading activity as well as increased volatility.

Thus, the result of f3>0 confirms theoretical predictions of the overconfidence model and selfattribution bias model. Successful investments in the market will raise the confidence of traders and increase their trading activities excessively. Using the decomposition method in our analysis, we found that this phenomenon is not associated with the level of volatility per se, but forms one of its components, having a high influence on conditional variance. However, the most interesting and important conclusion was made using the comparison f3>f4. It means that volatility cannot be explained primarily with respect to liquidity or trading activities at the market as a whole, but mostly with regard to the behavioral component inherent in trading volume. Thus, this conclusion confirms the claims of Chuang & Lee (2006) and international findings from Jlassi et al. (2014), who suggest that overconfidence may act as one of the driving

ISSN: 2455-8834

Volume:11, Issue:08 "August 2026"

forces of clustered and excessive volatility. In regard to Vietnam, the high level of the OVER coefficient suggests that behavioral factors are one of the main drivers of market volatility.

Furthermore, the negative and significant value of the asymmetry coefficient is meaningful as well. The value of K<0 suggests that Vietnamese stock prices respond more positively to adverse shock than to favorable shock. The above findings coincide with existing empirical evidence in relation to asymmetric volatility and the leverage effect. Practically, it means that negative market sentiments trigger a sharp increase in volatility compared to positive market sentiments. As retail investors are predominant in Vietnam, the phenomenon could be attributed to panic selling and herding.

On the whole, the findings indicate that Vietnamese stock market is affected by behavioral overreactions and high levels of volatility, as well as asymmetric responses to shocks. As a consequence, Vietnamese stock market becomes highly sensitive to optimism and stress during which the overreaction effect occurs.

Even though a conclusion may review the main results or contributions of the paper, do not duplicate the abstract or the introduction. For a conclusion, you might elaborate on the importance of the work or suggest the potential applications and extensions.

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