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Impact of overconfidence, optimism, pessimism and herd mentality on trading volume in Vietnam's stock market

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Abstract

This study investigates the impact of overconfidence, optimism, pessimism, and herd mentality on trading volume in the Vietnamese stock market. Using daily VN30 index price and trading volume data from January 1, 2020, to June 30, 2024, the study employs Wavelet Transform, Spillover Index, and Spectral Granger Causality tests to explore the dynamic relationships between investor sentiment and trading activity. The results reveal that overconfidence has a relatively minor impact, whereas optimism significantly increases trading activity during bull markets. In contrast, pessimism and herd mentality strongly influence trading volume across all market conditions. Optimism amplifies herd behavior, fostering investor confidence, while pessimism weakens market stability by transmitting negative sentiment signals. These findings highlight the importance of incorporating psychological factors into market analysis to enhance predictive accuracy. Understanding these behavioral influences enables investors and policymakers to develop strategies that mitigate sentiment-driven volatility, promote rational investment decisions, and improve financial market stability.

Keywords: Behavioral finance, emerging markets, herd mentality, optimism, overconfidence, pessimism, trading volume.

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1. Introduction

The stock market has become an increasingly attractive investment channel, particularly in the aftermath of the COVID-19 pandemic. Its accessibility and suitability for a broad range of investors, coupled with the potential for substantial trading profits—especially when utilizing financial leverage—have driven heightened participation. However, as with any form of investment, higher returns are inherently accompanied by greater risks. Many investors have faced significant losses, highlighting the importance of understanding the psychological aspects that influence investment decisions. According to

Schwager [1], Schwager [2], Schwager [3], and Schwager [4], investor psychology is a crucial determinant of success or failure in the stock market. Moreover, investors' psychological states directly shape their decisions and actions. Notably, market participants tend to exhibit similar psychological patterns in analogous situations, often leading to collective trading behaviors that influence price movements and trading volume [5]. Consequently, studying investor psychology in the stock market is essential for explaining past trends, predicting future market movements, and enabling investors to formulate strategic plans and manage investment risks more effectively.

Recent studies have increasingly examined the impact of psychological factors on stock market trading volume, reinforcing their critical role in market dynamics. Research by Dhaoui et al. [6], Oprean [7], Barberis [8], Hu et al. [9], Asghari et al. [10], and Rashid et al. [11], underscores the significance of behavioral influences on trading activity.

As a relatively young and evolving financial market, the Vietnamese stock market differs from its more established global counterparts in structure, stability, and investor behavior. Despite the disruptions caused by the COVID-19 pandemic, the market has shown remarkable recovery and growth, attracting a substantial influx of new investors. However, this trend introduces additional challenges to market stability. New investors, typically less experienced in managing emotions and psychological biases, are more susceptible to making impulsive decisions based on immediate emotional reactions. As the proportion of novice investors increases, the impact of psychological factors on market fluctuations intensifies [5].

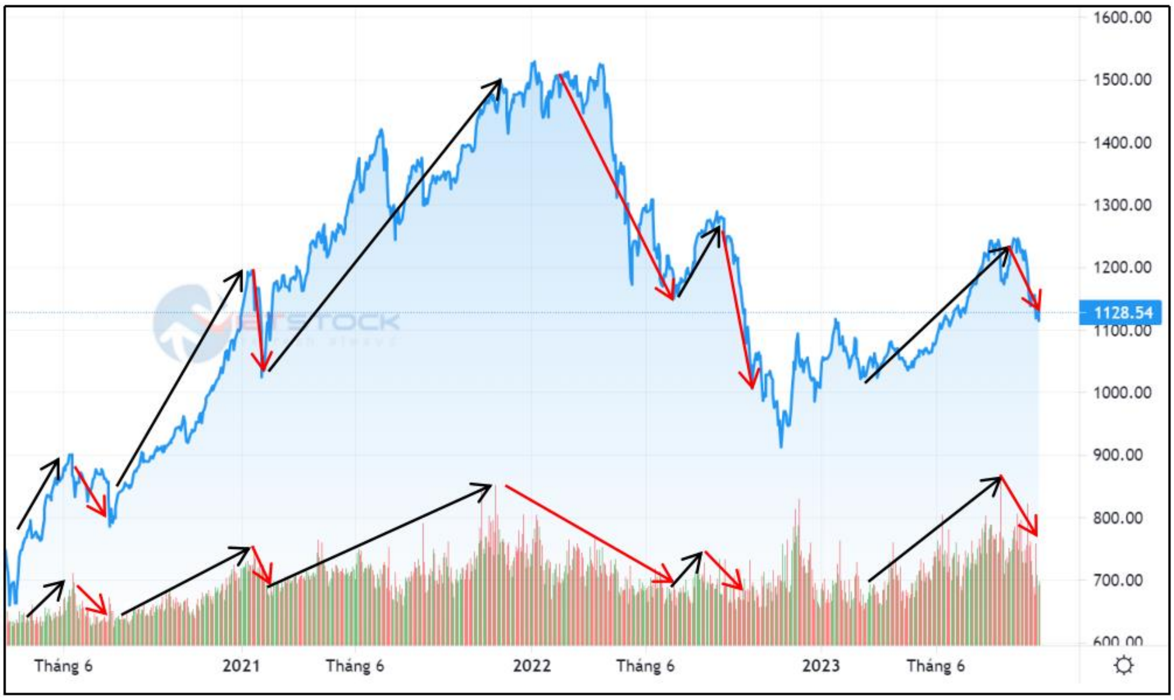


Figure 1.
VN-Index developments and investor trading volume by day (2020-2024).

Stock market price fluctuations influence investor psychology differently across market cycles. These psychological shifts, in turn, impact investors' buying and selling decisions, with trading volume serving as a direct reflection of these behavioral changes. Figure 2 illustrates the correlation between price fluctuations and trading volume in the Vietnamese stock market. To achieve sustainable long-term returns, investors must look beyond price trends and consider market psychology, which is reflected in trading volume dynamics [12, 13]. Understanding the relationship between psychological sentiment and trading volume provides investors with valuable insights for refining their investment strategies and risk management approaches.

2. Related Literature

For decades, financial and economic theories have traditionally assumed that market participants—including individuals, institutions, and even entire markets—act rationally [14]. According to these models, investors make unbiased decisions to maximize their utility, and those who make suboptimal choices receive lower returns. Over time, market forces naturally eliminate irrational investors, as they either learn to make better decisions or exit the market. Additionally, these theories assume that individual decision-making errors are uncorrelated and thus do not collectively influence market prices [15].

However, these assumptions impose unrealistic constraints on human behavior. Subsequent research in psychology has demonstrated that investor decision-making is heavily influenced by psychological biases and cognitive distortions [16]. Behavioral finance has emerged as a crucial framework for understanding stock market anomalies that traditional economic models fail to explain [17]. Among the most significant psychological biases affecting stock market investors are overconfidence, optimism, pessimism, and herd mentality [18, 19].

2.1. Overconfidence and Trading Volume

Overconfidence bias leads investors to underestimate the variance of risky assets and overestimate their predictive accuracy [20]. Theoretical models suggest that overconfidence increases market trading volume, as overconfident investors trade more aggressively than their less confident counterparts [21, 22]. Empirical studies further confirm that overconfident investors execute more trades [23], place a higher proportion of unprofitable orders [24] and perceive their investment skills as superior, prompting excessive trading [25].

Cultural differences also influence overconfidence. Yates, et al. [26] found that Chinese investors exhibited higher levels of confidence than Americans, while Americans were more confident than Japanese investors. Similarly, Acker and Duck [27] found that Asian investors demonstrated greater overconfidence than British investors. However, the effect of overconfidence on trading behavior varies across countries. For instance, overconfidence had no discernible effect on investors in Sri Lanka [28] or Tunisia [29] whereas it significantly influenced individual investors in Malaysia Bakar and Yi [30]. Xia and Madni [31] provided evidence that overconfidence strongly affects Chinese investors, as increased confidence correlates with higher trading volume. Similarly, Rashid, et al. [11] found that greater investor confidence led to increased trading activity. These findings suggest that while overconfidence generally contributes to higher trading volume, its impact is subject to cultural and market-specific variations.

2.2. Optimism, Pessimism, and Risk Attitudes

Investor sentiment—manifesting as optimism or pessimism—plays a crucial role in shaping risk attitudes. According to Quiggin [32], pessimistic investors exhibit risk aversion in profitable situations and risk-seeking behavior when facing losses, whereas optimistic investors display the opposite tendencies. Investors' risk attitudes directly affect trading volume; risk-averse investors prioritize certainty, leading to lower trading volumes, while risk-seeking investors engage in more frequent trading [33].

Several studies confirm the significant influence of optimism on trading behavior. Arik and Sri [34] demonstrated that investor sentiment, particularly optimism, strongly affects trading decisions. Excessive optimism increases risk tolerance [35] leading to higher trading volumes [36]. However, the impact of optimism varies across markets. Rashid et al. [11] found that in the Pakistani stock market, trading volume decreased when investors were optimistic but increased when they were pessimistic. Similarly, Dhaoui and Khraief [37] observed that pessimism exerted a far greater influence on price trends and trading volume in the French financial market than optimism.

Dhaoui and Bacha [38] further showed that market liquidity responds asymmetrically to investor sentiment. In the short term, liquidity reacts sharply to overconfidence, while optimism and pessimism have negligible immediate effects on trading volume. However, in the long run, these sentiments significantly shape market trends. Andleeb and Hassan [39] found that optimism and pessimism strongly influence conditional volatility in emerging stock markets, including Brazil, India, Pakistan, Russia, Indonesia, South Africa, and China. These findings highlight the complex and often contradictory effects of investor sentiment on trading behavior, reinforcing the need for market-specific analyses.

2.3. Herd Mentality and Market Volatility

Herd mentality refers to investors' tendency to follow collective behavior, often resulting in synchronized trading patterns [40]. Psychological studies suggest that emotions and decision-making processes become contagious in group settings, leading individuals to act impulsively and conform to prevailing market trends, regardless of their level of financial knowledge [41]. Market conditions influence herd behavior, with greater volatility amplifying its effects [42].

Empirical research on herd mentality yields mixed results across different markets. While De Bondt and Forbes [43] found strong evidence of herding behavior in the UK stock market, Demirer and Kutan [44] found no significant herding effect in China. Similarly, Chang, et al. [45] reported no evidence of herd behavior in the US and Hong Kong stock markets but observed substantial herding in Japan, South Korea, and Taiwan. Herd mentality is a powerful driver of trading volume [28] often exacerbating market fluctuations independent of macroeconomic fundamentals [46].

The intensity of herd behavior also varies depending on market conditions. Kyriazis [47] found that herding is more pronounced during extreme market events, particularly in bullish markets, whereas Vieito, et al. [48] demonstrated that herd mentality persists across all market phases. These findings suggest that while herd behavior is a universal market phenomenon, its prevalence and impact differ across financial environments.

2.4. Implications for the Vietnamese Stock Market

The existing literature underscores that overconfidence, optimism, pessimism, and herd mentality exert varying degrees of influence on investor behavior and trading volume, depending on market structures and cultural contexts. Given these differences, this study seeks to reassess the impact of these psychological factors on Vietnamese investors and their trading behavior. By examining these behavioral dynamics, the study aims to provide insights that can inform tailored policy recommendations to enhance market stability and investor decision-making in Vietnam's evolving stock market.

3. Methodology

3.1. Data and Variables

This study examines the impact of overconfidence, optimism, pessimism, and herd mentality on trading volume in the Vietnamese stock market. The analysis utilizes daily time-series data spanning from January 1, 2020, to June 30, 2024. The dataset includes price and trading volume data for the VN30 index and its constituent stocks, sourced from Investing.com. The description and measurement of the study variables are presented in Table 1 below.

Table 1.
Description and measurement of study variables.

Symbol	Variable description	Measurement	Source
$\ln(TV_t)$	Trading volume	Nepe logarithm of trading volume of VN30 index on day t $TV_t = \ln(TV_t)$	Bakar and Yi [30]
$over_t$	Overconfidence	Calculated through the price and trading volume of component stocks i of the VN30 index on day t $over_t = a_t$ trong $Ln(TV_{i,t}) = a_t \cdot R_{i,t-1} + b_t$ $R_{i,t-1} = \ln\left(\frac{P_{i,t-1}}{P_{i,t-2}}\right)$	Rashid, et al. [11]
$optim_t$	Optimism	Calculated through the closing prices of component stocks i of the VN30 index on day t $optim_t = \frac{1}{N}\sum_1^N (RR_{i,t} \mid RR_{i,t} > E[RR_i])$ $RR_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}}$	Dhaoui, et al. [6] and Rashid, et al. [11]
$pessim_t$	Pessimism	Calculated through the closing prices of component stocks i of the VN30 index on day t $pessim_t = -\frac{1}{N}\sum_1^N \left(RR_{i,t} \mid RR_{i,t} < E[RR_i]\right]$ $RR_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}}$	Dhaoui, et al. [6] and Rashid, et al. [11]
$herd_t$	Herd mentality	Calculated through the beta coefficient in the CAPM model of component stocks i of the VN30 index and the VN30 index at day t $herd_t = 1 - \exp(H_{mt})$ $\begin{cases} \mathrm{Log}\left[\mathrm{Std}_c\left(\beta^b_{imt}\right)\right] = \mu_m + H_{mt} + \vartheta_{mt}, & \vartheta_{mt} \sim \mathrm{iid}(0, \sigma^2_{m\upsilon}) \\ H_{mt} = \phi_m H_{mt} - 1 + \eta_{mt}, & \eta_{mt} \sim \mathrm{iid}(0, \sigma^2_{m\eta}) \end{cases}$	Hwang and Salmon [46]

3.2. Measurement of Psychological Variables

Investor behavior is influenced by past returns, market expectations, and collective market sentiment. The key psychological variables—overconfidence, optimism, pessimism, and herd mentality—are measured as follows:

3.2.1. Overconfidence ($over_t$)

According to Rashid et al. [11], past returns affect investor confidence, which in turn influences trading volume. Overconfidence is measured by analyzing the degree to which past returns impact current trading volume. Specifically, if investors overestimate their predictive accuracy, they tend to increase trading volume following prior gains.

3.2.2. Optimism ($optim_t$) and Pessimism ($pessim_t$)

Following Dhaoui et al. [6] optimism arises when stock prices increase abnormally or exceed their expected values over a given period, whereas pessimism manifests when stock prices fall below their expected values. Rashid et al. [11] further refine this measurement by defining the threshold for optimism as the sum of the average return and its standard deviation over the study period.

In this study, optimism and pessimism are quantified by comparing actual stock returns to the average return of the research period. Optimism occurs when the actual return surpasses the average return, while pessimism arises when the actual return falls below the average.

3.2.3. Herd Mentality ($herd_t$)

Hwang and Salmon [46] introduced a methodology to quantify herd behavior by examining deviations from equilibrium expectations in the CAPM pricing model. Their approach isolates the herding effect embedded in observed asset returns, acknowledging that herd mentality leads to mispricing as rational investment decisions become constrained by biased collective beliefs.

The herding measure is computed by analyzing the relative dispersion of stock betas (β) in the CAPM model, which reflects the extent to which investors disregard fundamental valuation principles in favor of collective trading behavior.

3.3. Justification for Data Selection

This study focuses on VN30 index stocks due to their liquidity and market influence. The VN30 index represents the 30 most liquid stocks on the Ho Chi Minh Stock Exchange (HOSE), making it a suitable proxy for investor sentiment and trading activity in Vietnam. Unlike smaller-cap stocks, VN30 stocks are widely followed by institutional and retail investors, providing a robust dataset for examining psychological effects on trading volume.

By employing daily time-series data and rigorous econometric techniques, this study aims to provide empirical insights into how investor sentiment influences trading behavior in Vietnam's evolving stock market.

4. Methodology

4.1. Wavelet transform method

This study employs the Wavelet Transform (WT) to analyze time-series data, as the predicted values are functions of both time and spatial coordinates. Traditional methods, such as the Fourier Transform, initiated by Joseph Fourier in the 1800s, have been widely used to convert signals from the time domain to the frequency domain. However, Fourier analysis assumes a static frequency spectrum, which limits its applicability to dynamic, non-stationary financial time series.

To overcome these limitations, this study utilizes the Wavelet Transform (WT), first introduced by Goupillaud et al. [49], which enhances accuracy and has broad applicability in financial research. The Wavelet approach is particularly effective for analyzing non-stationary data, as it provides high resolution in both the frequency and time domains, identifying when specific frequencies occur and how they evolve over time. This method allows for a three-dimensional analysis of correlations between variables, incorporating time, frequency, and correlation strength.

Wavelet Transform decomposes a time series x(t) into two components: the time domain and the frequency domain. Torrence and Webster [50] developed the Cross-Wavelet Transform (CWT) to examine the correlation between two time series x(t) and y(t) within the same time-frequency space. The CWT is mathematically represented as:

$$W_n^{XY}(\mathrm{u,s}) = W_n^X(u,s)W_n^{Y*}(u,s)$$

In there:

u represents the time position

s represents the wavelength corresponding to each frequency domain,

* denotes the complex conjugate

W is the transformation function that converts a continuous time series into wavelets.

Furthermore, Bloomfield et al. [51] introduced the Wavelet Phase-Difference Technique to measure dependence and causality between time series, expressed as:

$$\varphi_{xy} = tan^{-1}(\frac{\Im\left\{\mathrm{S}\left(s^{-1}W_{xy}(u,s)\right)\right\}}{\Re\left\{\mathrm{S}\left(s^{-1}W_{xy}(u,s)\right)\right\}})$$

In there:

$\Im$ represents the imaginary component of the CWT

$\Re$ represents the real component of the CWT

φ_{xy} varies within the range $[-\pi,\pi]$

The phase relationship is visually represented by arrow notations in Wavelet analysis:

($\boxed{\searrow}$) (down-right): The second variable leads, the first follows (positive correlation).

($\boxed{\nwarrow}$) (up-left): The second variable leads, causing an opposite effect on the first variable.

($\boxed{\nearrow}$) (up-right): The first variable leads, positively affecting the second variable.

($\boxed{\swarrow}$) (down-left): The first variable leads, negatively affecting the second variable

4.2. Spillover Index Model

To quantify the dynamic interactions between overconfidence, optimism, pessimism, herd mentality, and trading volume, this study applies the Spillover Index proposed by Diebold and Yilmaz [52] which is built upon a Vector Autoregressive (VAR) Model.

Step 1: Estimation of the VAR Model

The VAR(p) model is estimated with an optimal lag p:

$$x_i = \sum_{i=1}^{p} \emptyset_i y_{t-i} + \varepsilon_i$$

Where: x_i is a vector of endogenous variables; $\emptyset_i$ is an N × N parameter matrix; $\varepsilon_i \sim (0,\Sigma)$ represents white noise disturbances.

The corresponding moving average representation is:

$$x_t = \sum_{p=0}^{\infty} A_i \varepsilon_{t-i}$$

Where: A_i is the coefficient matrix, defined as $A_i = \theta_1 A_{i-1} + \theta_2 A_{i-2} + \cdots + \theta_p A_{i-p}$, A_0 is an N × N identity matrix and $A_i = 0$ for all i < 0.

Step 2: Variance Decomposition for Forecasting Horizon H

The variance decomposition for the forecast error over H periods is:

$$\emptyset_{ij}^{\delta}(H) = \frac{\sigma_{ij}\sum_{h=0}^{H-1}(e_i' A_h \sum e_i)^2}{\sum_{h=0}^{H-1}(e_i' A_h \sum A_h' e_i)}$$

where: $\theta_{ij}^{\delta}(H)$ represents the variance decomposition component,

Normalization ensures that:

$$\tilde{\theta}_{ij}^{\delta}(H) = \frac{\theta_{ij}^{\delta}(H)}{\sum_{j=1}^{N} \theta_{ij}^{\delta}(H)}$$

The total spillover index is:

$$S^{\delta}(H) = \frac{\sum_{i,j=1,j\neq 1}^{N} \tilde{\theta}_{ij}^{\delta}(H)}{N} \times 100$$

where a value close to 0 indicates weak spillover effects, and a value close to 100 suggests strong spillover effects.

4.3. Breitung-Candelon Spectral Granger Causality Test

To validate the robustness of the empirical findings, this study employs the Breitung and Candelon [53] Spectral Granger Causality Test to assess the causal relationships between variables across different frequency domains.

The Spectral Granger Causality Test evaluates whether X_t Granger-causes Y_t at specific frequencies. Given a VAR(p) model:

$$\left(I_2 - A_1 L - \cdots - A_p L_p\right) Z_t = \varepsilon_t$$

In there:

L: is the lag operator

A_i: is a 2x2 lag matrix;

I_2: is the identity matrix

$\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})^T$ is the error vector with white noise components.

Using Fourier transforms, the spectral density function of Xt is:

$$f_X(\omega) = \frac{1}{2\pi}\{|\varphi_{11}(e^{-i\omega})|^2 + |\varphi_{12}(e^{-i\omega})|^2\}$$

Granger causality from Xt to Yt is quantified as:

$$M_{X\to Y}(\omega) = log\left\{\frac{2\pi f_X(\omega)}{|\varphi_{11}(e^{-i\omega})|^2}\right\}$$

If $\left|\varphi_{12}(e^{-i\omega})\right| = 0$, then $M_{X\to Y}(\omega)$: implying no causality at frequency ω

The test results across different frequency domains (e.g., short-run (0–1), medium-run (1–2), long-run (2–3)) indicate whether the causal relationships persist across different time horizons.

5. Empirical Results

5.1. Descriptive Statistics of Variables

The descriptive statistics for the research variables are summarized in Table 2.

Table 2.
Descriptive statistics of variables.

Variable	Medium	Standard deviation	Smallest	Biggest
lnTV	5.0714	0.4453	3.4828	6.1445
over	4.8487	32.4256	-82.7003	535.6645
optimize	0.0079	0.0077	0	0.0566
soccer	0.0074	0.0099	0	0.0692
herd	0.0680	0.0315	0.0036	0.6338

The descriptive statistics reveal notable variations across the research variables. The mean values of lnTV and over are relatively high, at 5.0714 and 4.8487, respectively, whereas the mean values of optim and pessim are significantly lower, at 0.0079 and 0.0074, respectively.

A key observation from the standard deviation values and the range between the minimum and maximum values is that the overoverover variable exhibits the highest degree of variability. Specifically, its values range widely from -82.7003 to 535.6645, indicating substantial fluctuations in investor overconfidence levels. In contrast, the remaining variables show relatively stable fluctuations, suggesting less extreme variations in optimism, pessimism, and herd behavior. The large dispersion in overoverover suggests potential outliers or a highly volatile nature of overconfidence in the market, which warrants further examination to ensure robustness in subsequent analyses.

5.2. Stationarity Test

Before conducting further econometric analysis, it is crucial to test whether the research variables exhibit stationarity, as non-stationary time series data can lead to spurious regression results. To assess stationarity, this study applies both the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test. The ADF test accounts for autocorrelation by including lagged differences, while the PP test is a modified version of the Dickey-Fuller test that corrects for heteroskedasticity and autocorrelation in the residuals.

Table 3.
Unit Root Test Results (ADF and PP Tests).

Variable	ADF	P-value	PP	P-value
lnTV	-9.462	0.0000	-8.249	0.0000
over	-23.376	0.0000	-22.673	0.0000
optimize	-30.163	0.0000	-30.104	0.0000
soccer	-32,994	0.0000	-32.681	0.0000
herd	-21.328	0.0000	-21.576	0.0000

The results of both ADF and PP tests, presented in Table 3, indicate that all research variables reject the null hypothesis of a unit root at the 1% significance level. This confirms that all variables are stationary at their original levels (I (0)), ensuring that they are suitable for further econometric modeling without the need for differencing.

It is worth noting that stationarity is a critical assumption when applying time-series models, such as the Spillover Index Model and Wavelet Transform Method, as non-stationary data can lead to biased or misleading inferences. Given the stationarity of all variables, the study proceeds with its analytical framework to examine the relationships between investor sentiment and trading volume dynamics in the Vietnamese stock market.

5.3. Wavelet Analysis Results

The results of the Wavelet Transform Coherence (WTC) analysis between overconfidence, optimism, pessimism, herd mentality, and trading volume reveal several key findings regarding the dynamic interactions between investor sentiment and market activity. The analysis indicates that pessimism and herd mentality exhibit strong correlations with trading volume across all market phases, while optimism is significantly correlated with trading volume primarily during bullish market conditions but has little association during neutral or bearish phases. Additionally, the findings suggest that overconfidence has a relatively weak correlation with trading volume over the research period.

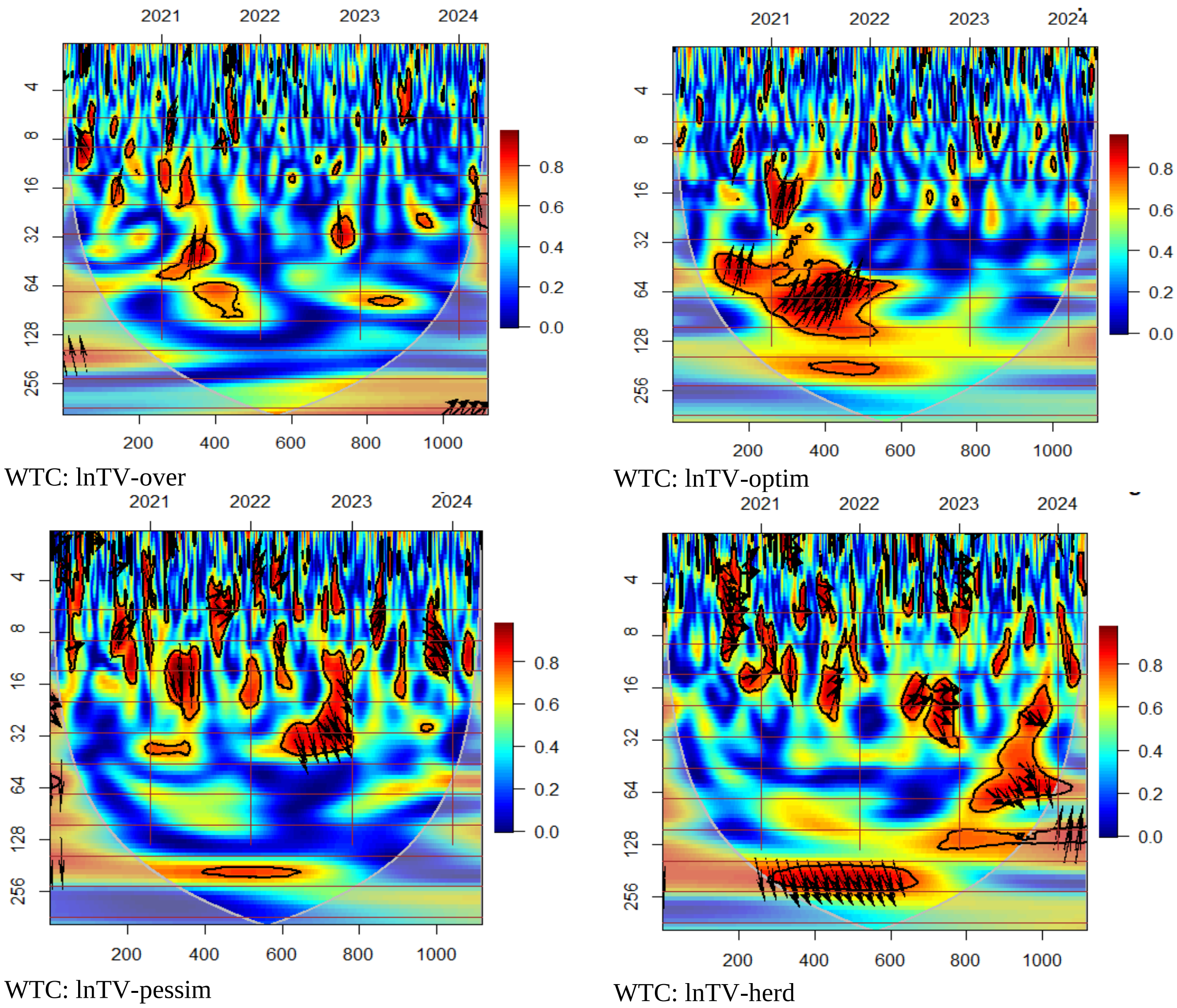


Figure 2.
Wavelet analysis results between overconfidence, optimism, pessimism, herd mentality and trading volume.

5.4. The Relationship Between Overconfidence and Trading Volume

The Wavelet Transform Coherence (WTC) analysis suggests that Vietnamese investors are less affected by overconfidence, which may be attributed to the high proportion of new and young investors in the market during the research period. New investors may lack the experience necessary to develop excessive confidence in their trading abilities.

Long-term impact: The presence of strong correlation zones at lower frequency bands indicates that overconfidence influences trading volume predominantly in the long term, as investors gain market experience over time.

Bull market effect (mid-2020 to Q3 2022): During this period of rapid market growth, the arrows in the WTC plots pointing up to the right (↗) indicate that higher trading volume reinforces investor confidence in both the short and medium term. This phenomenon aligns with behavioral finance theories, where gains in a bullish market strengthen investor confidence and increase trading activity.

Bear market effect (Q1 2020 & Q4 2022): During periods of sharp market declines, arrows pointing up to the left (↖) suggest that more confident investors tend to trade less. Confident investors are more likely to remain calm, avoiding panic-driven selling during downturns.

5.5. The Relationship Between Optimism and Trading Volume

The analysis reveals that optimism and trading volume are significantly correlated during prolonged market uptrends (mid-2020 to Q1 2022). This finding is consistent with Andleeb and Hassan [39] but contrasts with Rashid et al. [11], who reported that optimism reduces trading volume.

Medium- and long-term correlation: Optimism strengthens only when the market sustains growth over an extended period.

Directional influence: The presence of upward-right arrows (↗) in the WTC plots suggests that investors who engage in higher trading volume over extended periods tend to become more optimistic.

5.6. The Relationship Between Pessimism and Trading Volume

Unlike optimism, pessimism strongly influences trading volume across all market conditions (bullish, bearish, and neutral). The short-term dominance of this correlation suggests that pessimism-driven trading behaviors are often reactionary and event-driven, consistent with findings from Barberis [8], Dhaoui and Khraief [37], and Rashid et al. [11].

During bull markets (H2 2020) and sideways phases (Q3 2021 to Q1 2022), Pessimism emerges even when the market is performing well. The inability of the market to continue rising often leads to heightened pessimism, particularly among investors who fear a potential downturn.

During bear markets (H2 2022 & Q4 2023), Investors exhibit progressively increasing pessimism as the market declines.

Short-term reactions: The presence of short-term correlation zones suggests that negative news and market downturns rapidly trigger pessimistic sentiment, leading to increased trading activity.

5.7. The Influence Between Herd Mentality and Trading Volume

The findings indicate that herd mentality significantly influences trading volume across short, medium, and long-term horizons, aligning with Xia and Madni [31].

Behavioral drivers: The strong correlation between herd behavior and trading volume can be attributed to the high proportion of inexperienced investors in Vietnam's stock market. Many new investors follow market trends rather than relying on individual analysis, reinforcing the effect of herd behavior.

Bull market behavior (2021 to mid-2022): As the market continues to rise, investors become increasingly euphoric, leading to amplified trading activity. Enthusiasm spreads through herd behavior, reinforcing trading momentum.

Bear market behavior (2022 downturn): When market conditions deteriorate, panic-driven herd behavior dominates, triggering widespread selling pressure and further increasing trading volume.

Stable market phase (2023–present): The effect of herd mentality on trading volume is less pronounced in a relatively stable market, with its influence being more prominent in the long-term rather than short-term dynamics.

5.8. Interrelationship between Sentiment Variables

Investor sentiment factors not only correlate with trading volume, but they also influence one another. These interdependencies are visualized in Figure 3.

The interactions between optimism, pessimism, overconfidence, and herd mentality play a crucial role in shaping investor behavior and market dynamics. The results from the Wavelet Transform Coherence (WTC) analysis indicate that these psychological factors are interconnected, influencing each other over different time horizons and reinforcing specific trading behaviors. Understanding these interrelationships is essential for explaining how sentiment-driven trading decisions evolve and how investor psychology contributes to market fluctuations.

A key finding is the strong long-term correlation between optimism and herd mentality, suggesting that optimistic investors are more likely to engage in collective trading behaviors rather than relying on independent analysis. When investors hold a positive outlook on the market, they tend to follow prevailing trends, reinforcing sentiment-driven trading cycles. This effect is particularly pronounced in bullish market conditions, where increasing optimism amplifies herd behavior, leading to momentum-driven trading. As a result, optimism does not only reflect individual investor sentiment but also acts as a catalyst for collective decision-making, strengthening herding tendencies in financial markets.

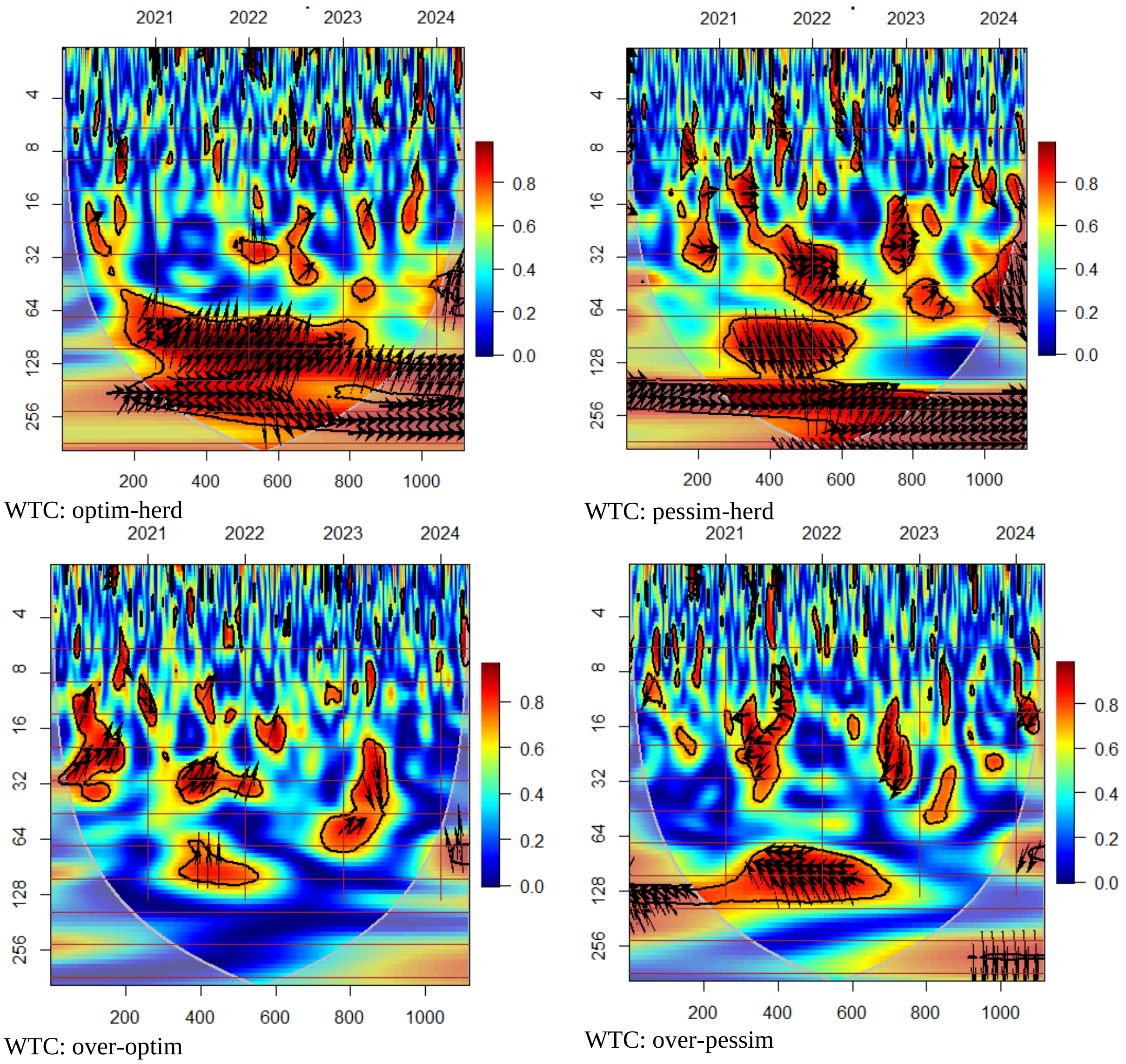


Figure 3.
Wavelet analysis results between overconfidence, optimism, pessimism, and herd mentality.

Similarly, pessimism exhibits a strong correlation with herd mentality across short, medium, and long-term horizons. However, the relationship is more complex and varies depending on the time frame. In the short and medium term, the presence of upward-right arrows (↗) in the WTC analysis suggests that pessimistic investors tend to follow the crowd, particularly during periods of heightened market uncertainty. This implies that negative sentiment spreads quickly, prompting reactionary trading behaviors and exacerbating market volatility. Over the long term, however, the analysis reveals downward-right arrows (↘), indicating that prolonged exposure to collective pessimism reinforces individual investor fear, leading to self-reinforcing cycles of negative sentiment. This phenomenon aligns with behavioral finance theories, which suggest that when investors witness widespread pessimism in the market, their own risk aversion increases, prompting further sell-offs and accelerating market downturns.

Beyond its relationship with herd mentality, overconfidence is found to be positively associated with optimism. Investors who exhibit higher levels of confidence tend to develop an increasingly optimistic outlook on market conditions, leading to greater risk-taking behaviors. This relationship suggests that overconfidence serves as a psychological driver of bullish sentiment, reinforcing speculative trading tendencies. In a market environment where investors are overconfident in their decision-making abilities, optimism becomes a self-reinforcing factor, potentially contributing to excessive trading activity and overvaluation of assets.

Conversely, pessimism has an adverse effect on overconfidence, particularly in the long term. The findings indicate that sustained exposure to negative market conditions diminishes investor confidence, as prolonged downturns provide continuous negative feedback, prompting investors to reassess their expectations and risk tolerance. Over time, market downturns erode investor overconfidence, leading to more cautious trading behavior. This observation supports existing behavioral finance literature, which posits that investors update their confidence levels based on their past experiences, adjusting their expectations as they encounter repeated market losses. The long-term impact of pessimism on confidence suggests that negative sentiment not only influences immediate trading decisions but also has a lasting psychological effect on how investors perceive risk and market opportunities.

In summary, the interplay between sentiment variables highlights the dynamic nature of investor psychology, where optimism strengthens herd mentality, pessimism reinforces self-reinforcing fear cycles, and overconfidence plays a pivotal role in shaping both optimism and pessimism. These interactions provide important insights into how psychological factors drive trading behavior, offering a deeper understanding of the mechanisms through which sentiment fluctuations impact financial markets. Recognizing these relationships is particularly relevant in emerging markets, such as Vietnam, where a high proportion of inexperienced investors may amplify sentiment-driven trading dynamics. By identifying these sentiment interdependencies, policymakers and market regulators can develop more effective risk management strategies to mitigate the impact of extreme investor sentiment on market stability.

5.9. Spillover Index Analysis Results

This section examines the transmission and reception spillover index over time for each research variable, providing insights into the extent and direction of volatility spillover effects. By calculating the bilateral spillover index, the study identifies the relative roles and interconnections of the psychological factors and trading volume in the model.

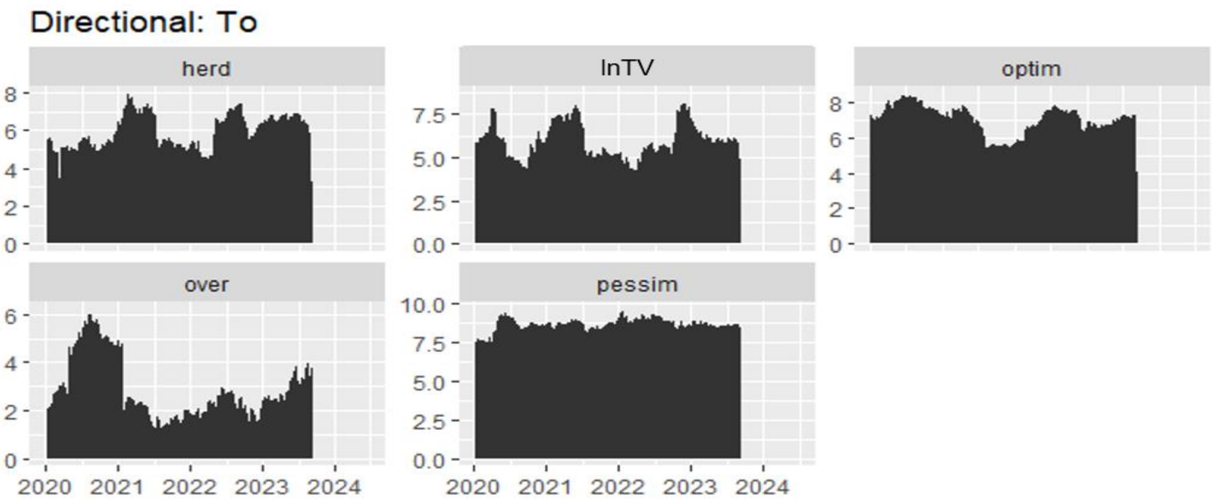


Figure 4.
Directional volatility spillover index, TO others.

The spillover index in the "TO" direction indicates the extent to which each psychological factor transmits volatility to other variables. The results reveal that pessimism consistently exhibits the highest transmission index across the entire research period, regardless of the level of market volatility. This suggests that pessimism is a persistent and influential factor, exerting significant effects on other psychological factors as well as investor trading volume across all market phases. These findings reinforce the results obtained from the Wavelet Transform Coherence (WTC) analysis, confirming that pessimistic sentiment plays a dominant role in shaping market sentiment and trading behavior.

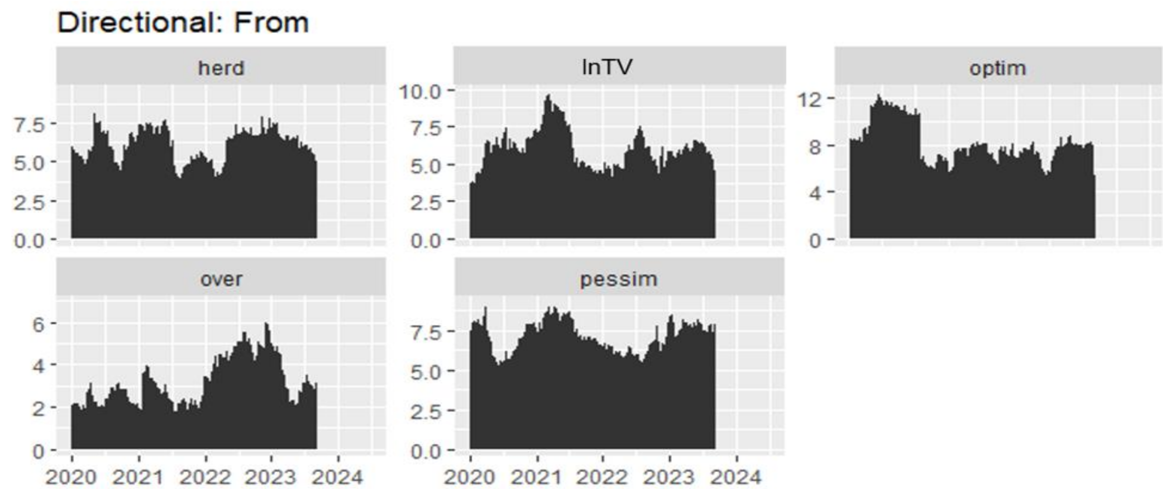


Figure 5.
Directional volatility spillover index, FROM others.

A notable pattern emerges among herd mentality, optimism, and trading volume, as their spillover indices increase during periods of heightened market volatility and decrease when market fluctuations subside. This indicates that these factors are highly sensitive to external shocks, amplifying investor reactions during turbulent market conditions. In contrast, overconfidence exhibits a distinct transmission pattern, with its spillover index rising significantly during bull markets but declining during bearish or sideways market conditions. This suggests that overconfidence exerts a strong influence only when market optimism prevails, while its impact diminishes when market sentiment weakens or stabilizes.

To further explore the dependence of each variable on the remaining factors, the study examines the spillover index in the "FROM" direction, as illustrated in Figure 5.

The spillover index in the "FROM" direction reflects the extent to which each variable is affected by external factors. The results indicate that trading volume and optimism exhibit high sensitivity during periods of rapid market expansion, with their spillover indices peaking in bullish market phases. However, during market downturns or sideways movements, their dependence on external influences declines, suggesting that optimism and trading activity are primarily driven by positive market conditions rather than external shocks during bearish phases.

Herd mentality, in contrast, demonstrates a strong reaction to market volatility, regardless of whether the market is in an uptrend or downtrend. The spillover index for herd behavior remains elevated during highly volatile periods, such as 2020 to mid-2021 and mid-2022 to the present, indicating that herding tendencies intensify when market uncertainty is high. However, during stable market conditions, the spillover index declines, implying that investors are less likely to engage in herd-driven trading during periods of lower volatility.

A particularly noteworthy finding concerns the spillover index of pessimism in the "FROM" direction. The results show that pessimism is highly reactive to other factors following strong market gains, as indicated by its elevated spillover index from mid-2021 to mid-2023. This suggests that investors tend to become more pessimistic after witnessing substantial price increases, possibly due to concerns about potential market corrections or reversals.

Furthermore, the spillover index in the "FROM" direction for overconfidence displays a distinct pattern, rising only from 2022 onwards. This finding implies that investor confidence is less influenced by bullish market conditions but becomes more reactive to external factors during bearish and sideways markets. In other words, overconfidence remains relatively stable in upward-trending markets but is more susceptible to external sentiment shifts when market conditions deteriorate.

Overall, these spillover effects align with the Wavelet Transform Coherence (WTC) analysis, reinforcing the interdependencies between investor sentiment and trading volume across different market phases. The results highlight the dominant role of pessimism in shaping market sentiment, the volatility-dependent nature of herd mentality, and the conditional influence of overconfidence on trading behavior. These insights contribute to a deeper understanding of how psychological factors interact in emerging markets and influence market stability over time.

5.10. Granger Causality Test Results in Spectral Form

To further investigate the dynamic relationships between investor sentiment and trading volume, the study employs the spectral Granger causality test, which allows for an analysis of causal linkages across different frequency domains. This approach is particularly valuable in distinguishing between short-term (high-frequency) and long-term (low-frequency) influences, providing deeper insights into how sentiment-driven trading behavior evolves over time. The results of the test are presented in Figure 6.

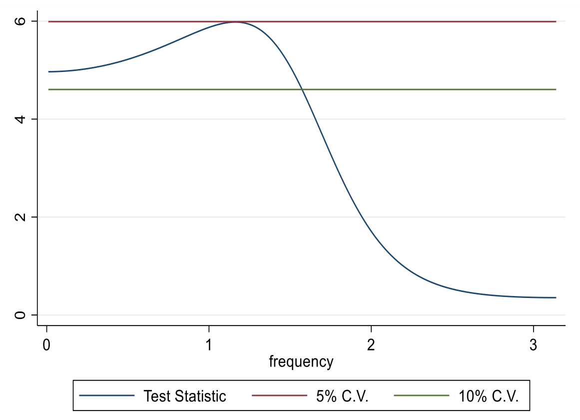
The results indicate that pessimism exhibits a significant Granger causal effect on trading volume, but only in the low-frequency domain, suggesting that pessimism influences trading volume primarily in the long run. This finding aligns with the earlier Wavelet Transform Coherence (WTC) analysis, reinforcing the idea that negative sentiment builds up gradually and exerts a prolonged effect on investor behavior. However, at higher frequencies (short-term effects), the test results reveal no significant Granger causality from pessimism to trading volume, implying that short-term fluctuations in pessimistic sentiment do not immediately drive trading activity.

In contrast, optimism and herd mentality do not exhibit a Granger causal effect on trading volume at either the 5% or 10% significance levels, across all frequency domains. This suggests that short-term fluctuations in optimism and herd behavior may be reactionary rather than predictive, meaning they respond to market conditions rather than actively driving changes in trading volume.

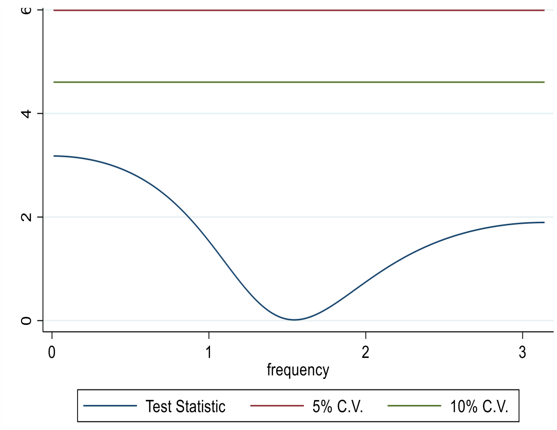
Regarding overconfidence, the results show no Granger causality at the 5% significance level, but a weak causal effect emerges at the 10% significance level in the low-frequency domain. This implies that overconfidence may have some influence on trading volume in the long run, although the effect is relatively weak compared to other psychological factors. This finding supports previous research indicating that overconfidence tends to develop gradually over time as investors accumulate market experience, rather than triggering immediate trading responses.

The spectral causality test results highlight the importance of distinguishing between short-term and long-term influences in behavioral finance. The findings suggest that: (1) Pessimism plays a long-term role in shaping trading volume dynamics, confirming that investor concerns and risk aversion build up over time, leading to sustained market impacts. (2) Optimism and herd mentality do not exhibit predictive power over trading volume, indicating that these sentiments are more likely reactive rather than causal in nature. (3) Overconfidence has a weak but statistically significant long-term effect, implying that its impact on trading activity emerges gradually rather than in response to immediate market changes.

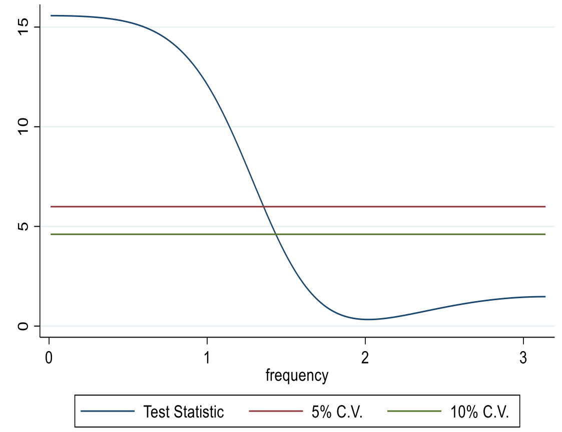
These insights provide further empirical evidence that investor psychology affects trading volume differently across time horizons, underscoring the need for a frequency-specific approach when analyzing behavioral influences in financial markets. The findings also suggest that market regulators and policymakers should focus on managing the long-term psychological drivers of trading behavior, such as pessimism and overconfidence, to enhance market stability.



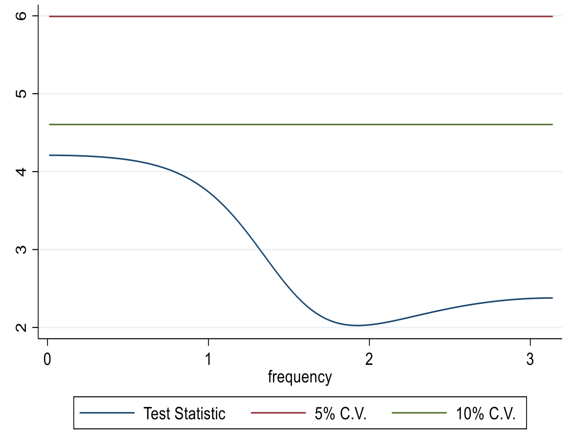
Spectral Granger-causality test: over-lnTV



Spectral Granger-causality test: optim-lnTV



Spectral Granger-causality test: pessim-lnTV



Spectral Granger-causality test: herd-lnTV

Figure 6.
Spectral Granger Causality Test Between Trading Volume and Psychological Factors.

6. Conclusion

The findings of this study underscore the significant influence of psychological factors on trading volume, as well as the reciprocal effect of trading activity on investor sentiment. Furthermore, these psychological states do not operate in isolation but rather interact dynamically, shaping market behavior in complex ways. Given these interdependencies, policy implications and investment strategies should account for the intricate relationships between psychological factors. Among the sentiment variables examined, pessimism and herd mentality exert the strongest influence on trading volume across all market phases, while optimism predominantly affects trading behavior during bullish periods.

While confidence is a valuable trait for investors, excessive confidence—or overconfidence—can lead to suboptimal decision-making and increased trading risks. To mitigate the adverse effects of overconfidence, investors should adopt a critical thinking approach, frequently re-evaluating their investment judgments. They should cultivate a mindset of continuous learning, acknowledging that financial markets are dynamic and that past successes do not guarantee future performance. Moreover, confidence should be built upon disciplined trading strategies rather than short-term returns, ensuring a more rational and structured investment approach.

Similarly, optimism can provide psychological resilience in volatile markets; however, excessive optimism may impair trading efficiency, particularly during bull markets when investors become overly euphoric. The analysis results indicate that investors tend to be more influenced by optimism during prolonged market uptrends, which can lead to overtrading and risk mismanagement. Therefore, investors should adopt a more skeptical and measured approach, particularly in seemingly ideal market conditions, and ensure that their trading volume remains proportional to their capital size and risk tolerance.

The study also highlights that investor are highly susceptible to pessimism, which can drive panic selling and reactionary trading behavior. To counteract the negative effects of pessimism, investors should develop well-defined trading plans and adhere to disciplined investment principles before executing trades. Additionally, practicing patience and reducing the frequency of portfolio monitoring can help investors avoid emotional decision-making and maintain a long-term perspective.

Herd mentality is another critical driver of trading volume, with investors often following collective trends rather than making independent decisions. While engaging with investment communities or trading groups can enhance market knowledge and skill development, investors should maintain objectivity and avoid making impulsive decisions based on crowd behavior. One effective strategy is to conduct personal analysis and establish trading plans independently before market sessions begin, thereby minimizing external distractions and emotional biases during active trading hours. Discussions and strategy reviews can be conducted outside of trading hours to ensure that investment decisions are made based on rational assessment rather than herd-driven sentiment.

In conclusion, the findings of this study confirm that investor psychology is highly complex and exerts varying degrees of influence on trading volume across different market conditions. To achieve long-term success in the stock market, investors must develop a deep understanding of psychological biases and actively implement self-regulation strategies to mitigate their impact. By integrating behavioral insights into their trading decisions, investors can enhance risk management, improve decision-making, and navigate market fluctuations with greater confidence and stability.

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