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OVERCONFIDENCE VS. HERDING: ANALYZING INVESTOR BEHAVIOR IN THE MOROCCAN RETAIL TRADE SECTOR

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Abstract:
This study investigates overconfidence and herding behaviors among retail investors in the Moroccan stock market, focusing on four major stocks from the retail trade sector—Autohall, Ennakl, Label Vie, and Total Maroc—over the period from March 2015 to January 2025. Using daily data, investor behavior is analyzed through regression and rolling-window methods. Overconfidence is examined by exploring how volatility and past returns influence trading volume, while herding is evaluated through the Cross-Sectional Absolute Deviation (CSAD) framework applied to both returns and trading volume.

The results provide strong evidence of overconfidence, particularly during periods of increased market volatility, indicating that investors tend to trade excessively when uncertainty rises. Rolling analyses further reveal that overconfidence is time-varying and intensifies under volatile market conditions. In contrast, herding behavior is largely absent, as market dispersion tends to widen rather than contract during periods of high activity. Overall, the findings suggest that Moroccan retail investors are primarily guided by individual confidence rather than collective market sentiment.

Keywords: Overconfidence, Herding Behavior, Trading Volume, Behavioral Finance, Moroccan Stock Market.

1. Introduction

Investment decisions are often assumed to follow rational analysis, balancing risk and expected returns. In reality, psychological factors play a big role in decisions. Two main forces, overconfidence and herding, strongly shape how individuals and markets behave (Zainul et al., 2021). Overconfidence reflects the tendency to overestimate one's knowledge and predictive ability. Investors frequently believe they can beat the market or anticipate the next winner, despite the uncertainty of outcomes (Benos, 1998; Kahneman & Riepe, 1998; Merkle, 2017; Nosić & Weber, 2010). This leads to excessive trading, reliance on intuition, and neglect of diversification or advice (Glaser et al., 2013; Kumar & Prince, 2022; Nair & Shiva, 2023; Larrick et al., 2007). Overconfident behavior amplifies volatility, generates bubbles, and increases costs (Daniel et al., 1998; Barber & Odean, 2000; Odean, 1998b; Pak & Chatterjee, 2016; Hsu, 2022).

Herding, by contrast, arises when investors imitate others rather than rely on their own judgment. In periods of uncertainty, the fear of missing out or fear of loss encourages individuals to follow the crowd, even against fundamentals (Patwarani et al., 2023; Huang et al., 2020). Professionals such as fund managers are also prone to this behavior, preferring not to stand apart. Beginners are especially vulnerable, often copying strategies without fully understanding them (Gavriilidis et al., 2020).

When overconfidence and herding combine, they can make markets unstable. In good times, overconfident investors buy more as prices rise, and herding makes this effect stronger, leading to bubbles. In downturns, both behaviors can speed up panic selling and sharp price drops. This mix has played a part in major financial crises like the dot-com bubble and the 2008 crash (Abhijith et Bijulal 2024).

Recognizing these psychological factors is important for investors and regulators. Overconfidence encourages risk-taking beyond rational limits, while herding spreads collective errors across markets. Awareness of these forces improves the understanding of whether price changes reflect genuine value or collective emotion (Benayad et al., 2020; Abhijith et Bijulal 2024).

In Morocco, where financial markets are still developing, these patterns are still underexplored. As the country becomes more connected to global markets, investor psychology plays a bigger role in market stability and performance. This study looks at four major retail stocks: Autohall, Ennakl, Label Vie, and Total Maroc, to examine how overconfidence and herding affect trading in this setting.

2. Literature Review

2.1 Overconfidence Theory: Definition and Key Characteristics

Overconfidence is a central topic in behavioral finance, as it consistently shapes how investors make decisions. Odean (1998) was among the first to provide strong empirical evidence: his study of brokerage accounts revealed that overconfident investors trade far more than necessary, which reduces their returns due to higher transaction costs and poor market timing. Later works confirmed this effect, showing that excessive trading undermines both portfolio performance and market efficiency (Daniel et al., 1998; Barber & Odean, 2000).

Other studies extended these findings. Barber and Odean (2001) reported that men, on average, display greater overconfidence than women, resulting in more aggressive trading and lower risk-adjusted returns. Overconfidence also explains momentum investing, where investors assume that past success guarantees future gains, fueling short-term price rises disconnected from fundamentals (Daniel & Hirshleifer, 2015). Such behavior contributes to bubbles and price distortions.

In emerging markets, where information is scarcer and investors often lack advanced financial training, overconfidence tends to be amplified. Traders frequently overreact to news or short-term movements, producing higher volatility and weaker efficiency (Gervais & Odean, 2001; Hirshleifer & Shumway, 2023). This constant reactivity raises costs (Barber & Odean, 2000; Hirshleifer et al., 2023) and destabilizes markets. Combined with herding, it can create speculative bubbles that ultimately burst (Daniel et al., 1998; Halim & Pamungkas, 2023).

Recent research highlights that algorithmic and high-frequency trading can replicate the same risky patterns. Automated systems, like human investors, may pursue short-term profits at the expense of fundamentals, generating additional instability and abrupt market swings (Ali & Hirshleifer, 2017; Hirshleifer et al., 2023).

Although overconfidence is well documented in developed economies, less evidence exists for contexts like Morocco. With a large proportion of retail investors and generally modest financial literacy, the tendency to rely on intuition or short-term price signals appears stronger. Oukhouya et al. (2025) found that Moroccan investors often overestimate their ability to predict movements, privileging trends over company fundamentals. This study aims to deepen understanding of these dynamics in Morocco's retail sector.

2.2 Herding Behavior: Theory and Empirical Evidence

Herding occurs when investors imitate others rather than forming independent judgments, particularly in times of uncertainty (Hirshleifer & Teoh, 2003). Evidence of herding has been observed in advanced markets and in developing economies. Chiang and Zheng (2010) reported strong herding in China, Hong Kong, and South Korea, while Balcilar et al. (2017) and Economou (2016) identified similar behavior in oil-dependent economies and in countries such as Morocco and Nigeria during financial stress.

Herding is not limited to individuals. Fund managers sometimes follow market leaders to avoid reputational risks (Gavriilidis et al., 2020). In emerging markets, uncertainty, limited information, and institutional weaknesses reinforce this tendency (Balcilar et al., 2017). The Casablanca Stock Exchange offers a relevant case, as both retail and foreign participation have increased, while regulations continue to evolve.

Researchers usually measure herding through two approaches: trading activity, captured by the Cross-Sectional Absolute Deviation of Trading Volume (CSADV), and price co-movement, measured by the Cross-Sectional Absolute Deviation of Returns (CSAD) model (Chang, Cheng, & Khorana, 2000). These tools help identify moments when investors move collectively, ignoring fundamentals.

The interaction of herding with overconfidence further destabilizes markets. Together, these biases increase volatility, encourage bubbles, and reduce efficiency. This makes them particularly relevant in Morocco, where many retail investors are active.

Based on this literature, the present study pursues three objectives: first, to show how investor psychology affects Moroccan market dynamics; second, to provide insights for policymakers and investors; and third, to assess whether biases such as overconfidence and herding primarily undermine efficiency or occasionally create exploitable mispricing opportunities.

To structure the empirical investigation, the study formulates the following hypotheses:

- **H1:** Overconfidence increases trading volume, particularly following periods of strong returns and heightened volatility.
- **H2:** Investors exhibit herding in trading volume, resulting in lower dispersion (CSADV) during periods of heightened market-wide activity.
- **H3:** Investors herd in stock returns, producing lower return dispersion (CSAD) during extreme market movements.
- **H4:** Overconfidence amplifies herding in trading volume, as overconfident investors respond similarly to market signals.
- **H5:** Overconfidence and herding jointly contribute to market inefficiencies, generating short-term mispricing.

3. Methodology

This study takes a quantitative approach to explore how overconfidence and herding behavior influence trading volume and return dispersion in the Moroccan retail trade sector. In order to conduct this research work, we used regression models, rolling analysis, and different statistical tests.

The Odean (1998) model was selected for overconfidence because it directly links trading volume to volatility and past returns, providing a well-established measure of excessive trading driven by investor miscalibration. This approach has been widely applied in behavioral finance, especially in contexts where retail investors dominate. For herding, we follow Chang, Cheng, and Khorana (2000), whose CSAD framework improves upon earlier linear models (e.g., Christie & Huang, 1995) by capturing potential nonlinear effects between return dispersion and market returns. These two models remain standard in empirical research, ensuring comparability with international studies while being well-suited for testing behavioral biases in emerging markets like Morocco.

3.1 Overconfidence Analysis

3.1.1 Definition & Conceptual Framework

Overconfidence is when investors tend to overestimate their knowledge and ability to predict the market, which often results in more frequent trading. In this study, we explore overconfidence by looking at how trading volume relates to important factors like return volatility, past stock returns, and overall market returns.

3.1.2 Data Collection & Processing

The analysis focuses on daily stock prices and trading volumes of four companies in the retail trade sector listed on the Casablanca Stock Exchange: Autohall, Ennakl Automobiles, Label Vie, and Total Maroc. These companies were selected because they are among the most liquid and actively traded companies in the Moroccan retail trade sector. Their high turnover and data availability ensure reliable volume and price information, while their economic relevance to consumer spending makes them representative of retail investor activity. Focusing on these stocks avoids thinly traded securities that could bias results and allows us to capture sector-specific behavioral patterns. The data covers March 6, 2015, to January 28, 2025, providing a long-term view of market behaviors. All data was obtained from Investing.com, a trusted source for financial information.

The four stocks (Autohall, Ennakl, Label Vie, and Total Maroc) were ***Regression Model for Overconfidence***

To test for overconfidence, the following Ordinary Least Squares (OLS) regression model was applied (equation 1):

$$TV_{i,t} = \alpha + \beta\sigma_{i,t}^2 + \gamma R_{i,t-1} + \delta R_{m,t} + \epsilon_{i,t} \qquad (1)$$

Where:

- $TV_{i,t}$ = Trading volume for stock i at time t.
- $\sigma_{i,t}^2$ = Stock Return volatility, measured as the 30-day rolling variance of stock i.
- $R_{i,t-1}$ = Lagged stock return (to capture how past performance influences trading).
- $R_{m,t}$ = Market return, measured by the MASI index return.
- $\epsilon_{i,t}$ = Error term.

Each coefficient represents a specific relationship within the model:

- α (Intercept): Baseline level of trading volume when other variables are zero.
- β (Impact of volatility): If significantly positive, this suggests that high volatility stimulates trading, supporting overconfidence.
- γ (Impact of past returns): a positive value means that investors overreact to past returns, expecting trends to persist.
- δ (Effect of control variables): Captures external influences like liquidity shocks or economic announcements.

A notably positive β (volatility coefficient) highlights how overconfidence can boost trading activity, which might sometimes cause market mispricing (Daniel & Hirshleifer, 2015).

Hypothesis H1: Overconfidence leads to excessive trading volume, particularly following periods of high stock returns and volatility.:

- If $\beta > 0$, it indicates that investors trade more when volatility increases, consistent with overconfidence bias.
- If $\gamma > 0$, this situation means that past stock returns increase trading volume, confirming self-attribution bias (overconfident investors believe their past success was due to skill).
- If $\delta > 0$, market-wide movements impact trading behavior, in this case.

3.1.3 Rolling Regression for Time-Varying Overconfidence

To assess how overconfidence evolves over time, a 60-day rolling regression was performed (equation 2):

$$TV_{i,t} = \alpha_t + \beta_t \sigma_{i,t}^2 + \gamma_t R_{i,t-1} + \delta_t R_{m,t} + \epsilon_{i,t} \qquad (2)$$

Where:

- $TV_{i,t}$ = Trading volume for stock i at time t.
- $\sigma_{i,t}^2$ = Stock Return volatility, measured as the 30-day rolling variance of stock i.
- $R_{i,t-1}$ = Lagged stock return (to capture how past performance influences trading).
- $R_{m,t}$ = Market return, measured by the MASI index return.
- $\epsilon_{i,t}$ = Error term.

This rolling approach allows us to track fluctuations in overconfidence behavior across different market conditions.

We adopt 30-day and 60-day rolling windows to capture short- and medium-term dynamics of investor behavior. A 30-day window approximates one trading month and is sensitive to short-lived changes in sentiment, while the 60-day window (roughly a quarter) smooths daily fluctuations and highlights more persistent patterns. Using both horizons allows us to assess robustness and distinguish between temporary shocks and sustained behavioral tendencies.

3.2 Herding Behavior Analysis

Herding behavior happens when investors tend to follow market trends instead of doing their own independent analysis. To measure this, we use the Cross-Sectional Absolute Deviation (CSAD) metrics for trading volume and stock returns.

3.2.1 Herding in Trading Volume

The first step consists of computing the Relative Trading Volume (RTV) (equation 3):

$$RTV_{i,t} = \frac{TV_{i,t}}{\overline{TV_i}} \qquad (3)$$

Where $\overline{TV_i}$ is the mean trading volume of stock i over the entire sample.

Then we compute the Cross-Sectional Absolute Deviation of Trading Volume (CSADV (equation 4):

$$CSADV_t = \frac{1}{N}\sum_{i=1}^{N} \mid RTV_{i,t} - \overline{RTV_t} \mid \qquad (4)$$

Where $\overline{RTV_t}$ is the cross-sectional mean of RTV at time t.

In the third step, we estimate the Regression Model for Herding in Trading Volume (equation 5):

$$CSAD_t = \alpha + \beta_1 \mid MV_t \mid + \beta_2 MV_t^2 + \epsilon_t \qquad (5)$$

Where:

- MV_t = Total market trading volume.
- MV_t^2 = Squared market volume (to capture nonlinearity in dispersion).
- α (Alpha - Intercept Term)**:** Represents the baseline level of trading volume dispersion when market volume is zero. It captures any persistent dispersion that exists regardless of trading activity.
- β_1 (Sensitivity to Market Volume): The coefficient of total market trading volume (MV_t), measuring the impact of market activity on dispersion.
- β_2 (Nonlinear Effect - Sensitivity to Squared Market Volume): The coefficient of squared market volume (MV_t^2), capturing nonlinear relationships between market activity and trading dispersion.
-

Hypothesis H2: Investors exhibit herding behavior in trading volume, leading to lower dispersion (CSADV) during periods of high market-wide trading activity**:**

- If $\beta_2 < 0$, it indicates that CSADV decreases as market volume increases, which suggests herding behavior.
- If $\beta_2 \geq 0$, there is no evidence of herding in trading volume.

3.2.2 Herding in Returns

We start by computing the Log Returns (equation 6):

$$R_{i,t} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \qquad (6)$$

Where $P_{i,t}$ is the closing price of stock i at time t.

Then we calculate the CSAD for Returns (equation 7)

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N} \mid R_{i,t} - \bar{R}_t \mid \qquad (7)$$

Where $\bar{R}_t$ is the cross-sectional mean of individual stock returns.

In the next step, we compute the Regression Model for Herding in Returns (equation 8):

$$CSAD_t = \alpha + \beta_1 \mid R_{m,t} \mid + \beta_2 R_{m,t}^2 + \epsilon_t \qquad (8)$$

Where:

- $R_{m,t}$ = MASI index return.
- $R_{m,t}^2$ = Squared market return (to capture nonlinearity).

Hypothesis H3: Investors herd in stock returns, which lead to a lower dispersion of returns (CSAD) during periods of high market movements**:**

- If $\beta_2 < 0$, return dispersion decreases at high market movements, which indicates the presence of herding behavior.
- If $\beta_2 \geq 0$, return dispersion increases, suggesting investors act independently rather than herding.

3.2.3 Rolling t-Test for Herding Over Time

A 30-day rolling t-test was performed to analyze the time-varying nature of herding (equation 9):

$$t - statistic = \frac{\bar{X}}{s/\sqrt{n}} \qquad (9)$$

Where $\bar{X}$ is the mean coefficient for $R_{m,t}^2$ over a 30-day window, and s is its standard deviation.

- If the t-statistic remains below -2, it suggests herding is statistically significant.
- If the t-statistic is above -2, herding is weak or absent.

3.2.4 Data & Robustness Checks

To make sure our results are solid, we performed some helpful robustness checks:

1. Residual Normality Test: We used the Jarque-Bera test to see if the residuals follow a normal distribution.
2. Alternative Windows for Rolling Regressions: The study tried out 30-day and 60-day windows to double-check the robustness of the findings.

Hypothesis H4: Overconfidence amplifies herding behavior in trading volume, as overconfident investors react similarly to market signals.

- Interaction analysis: Examining periods of high volatility to see if herding in trading volume intensifies. Joint analysis of overconfidence (H1) and herding (H2): If trading volume increases due to overconfidence and dispersion decreases (CSADV), it suggests herding driven by overconfidence.
- Strong overconfidence coinciding with low CSADV values allow to confirm that Investors exhibit both biases simultaneously.
-

Hypothesis H5: Overconfidence and herding contribute to market inefficiencies, leading to short-term mispricing.

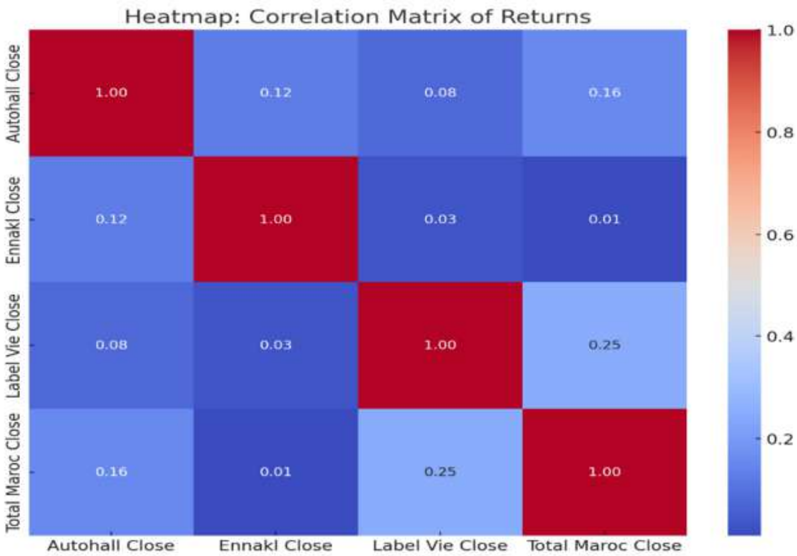
- Rolling regression & return dispersion analysis: Examining if high trading volume (overconfidence) and low dispersion (herding) coincide with market mispricing. Also, stock price deviations are compared from fundamental value in periods of extreme investor behavior.
- Periods of excess trading and low return dispersion linked to price anomalies provide evidence that behavioral biases can distort market outcomes.

4. Results and Discussion

This section presents the findings on overconfidence and herding behavior in the Moroccan stock market. The analysis starts with how overconfidence affects trading volume, then we assess herding behavior through trading volume and return dynamics. Finally, we look at how these two behavioral biases interact to give a complete view of investor behavior.

To measure how stocks in our sample move together, we calculate and visualize a correlation matrix of stock returns. The heatmap in Figure 1 shows how individual stocks move in relation to each other.

Figure 1: Heatmap: Correlation Matrix of Returns



The results in figure 1 show low correlations between the four stocks, indicating that investors tend to trade these stocks independently rather than collectively. This suggests herding behavior may be less prominent at the sector level. However, low correlation alone does not rule out behavioral biases like overconfidence, which often appear as increased trading volume rather than synchronized stock movements.

4.1 Overconfidence and Trading Volume

To test for overconfidence in the Moroccan stock market, we look at the relationships among trading volume, stock return volatility, past stock returns, and market conditions. Using the framework set by Odean (1998) and later studies, we apply the regression model:

$$TV_t = \alpha + \beta\sigma_t^2 + \gamma R_t + \delta X_t + \epsilon_t$$

We use this model to analyze four Moroccan retail stocks: Autohall, Ennakl, Label Vie, and Total Maroc, to see if investors are trading with signs of overconfidence.

4.1.1 Regression Analysis of Overconfidence and Trading Volume

Table 1 summarizes the regression results, showing how volatility, past returns, and market trends relate to trading in each stock.

Table 1. Regression Results for Overconfidence and Trading Volume

Stock	Constant	Volatility (β)	Lagged Return (γ)	Market Return (δ)	R-squared
Autohall	13900	-3.05E+06	-6.59E+04	-5.36E+04	0.003
Ennakl	3293	-4.35E+05	2027	-4.62E+04	0.002
Label Vie	1556	1.52E+06	-1.80E+04	-1611	0.022
Total Maroc	1498	6.17E+05	1222	414	0.016

Note: The coefficients are displayed in scientific notation where applicable.

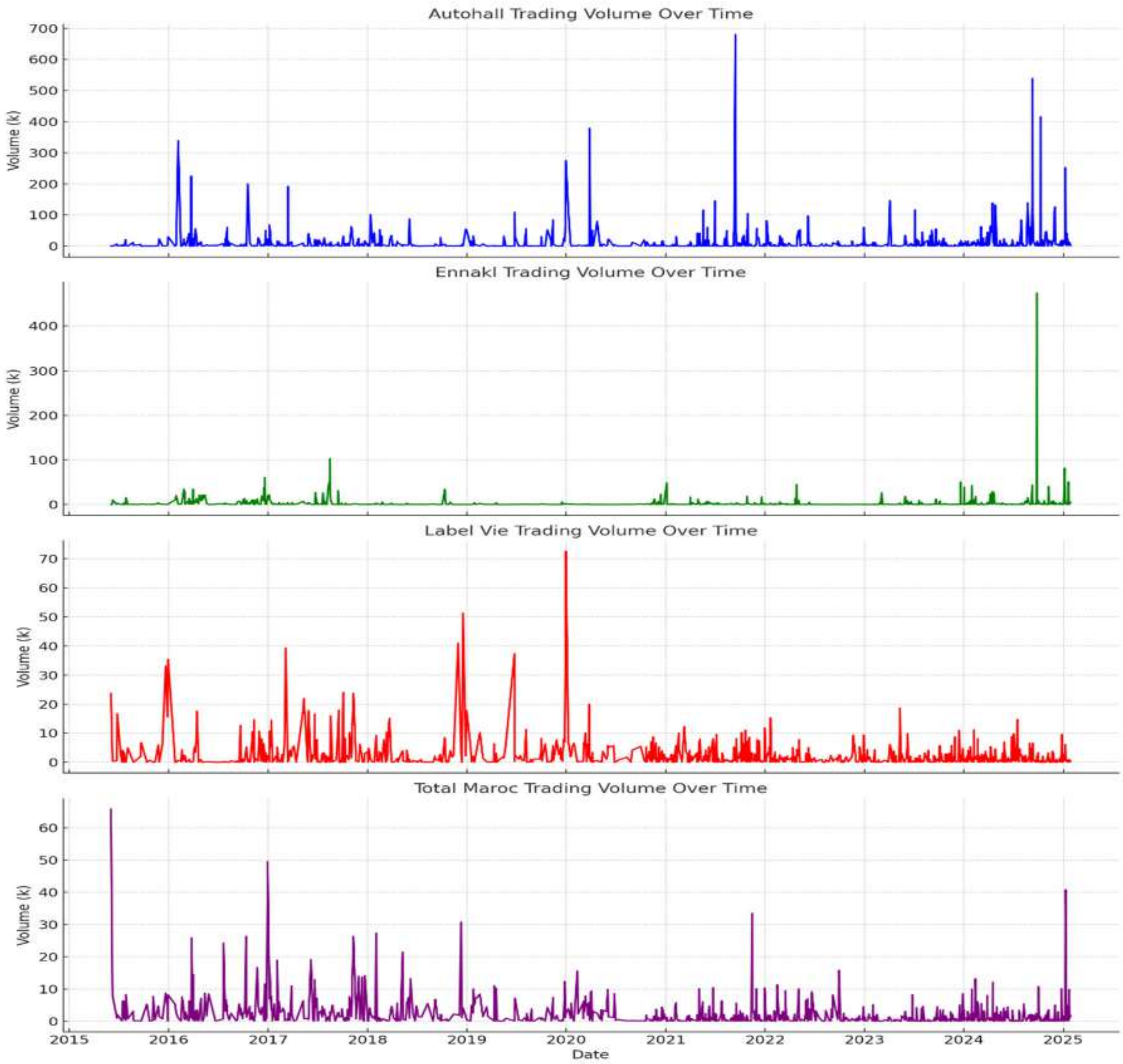
These results show that stock return volatility (β) is significantly positive for Label Vie and Total Maroc. This indicates that higher volatility is linked to increased trading volume in these stocks. It supports the idea that investors see volatility as an opportunity and engage in overtrading. In addition, market return (δ) is insignificant across all stocks, suggesting that overall market movements do not drive trading volume at the individual stock level. This means that investor behavior is more responsive to stock-specific factors than to broader market trends.

The results in Table 1 also reveal that lagged returns (γ) have mixed effects across stocks. While Label Vie shows a negative and statistically significant relationship, indicating that past performance discourages trading, the other stocks do not show a strong connection between past returns and trading volume. The R-squared values obtained are relatively low, suggesting that while volatility plays a role, other factors may also influence trading behavior.

Trading Volume Trends Over Time

A common sign of overconfidence is when investors tend to trade more often, believing they have better market insights and forecasting abilities (Odean, 1998). To explore this idea further, we looked at how trading volumes have moved over time for selected stocks in the Moroccan retail sector (Figure 2). This figure presents clear time-series charts that show how trading volume has shifted for each stock during the study period.

Figure 2. Trading Volume Over Time for Each Stock



The figure shows sharp spikes in trading volume, signaling bursts of speculative activity. These jumps typically coincide with significant events, earnings releases, or regulatory changes, indicating that investors react quickly to new informations. From a behavioral finance perspective, this surge in trading often reflects overconfidence; investors believe strongly in their own predictions and tend to trade more aggressively when opportunities seem to arise.

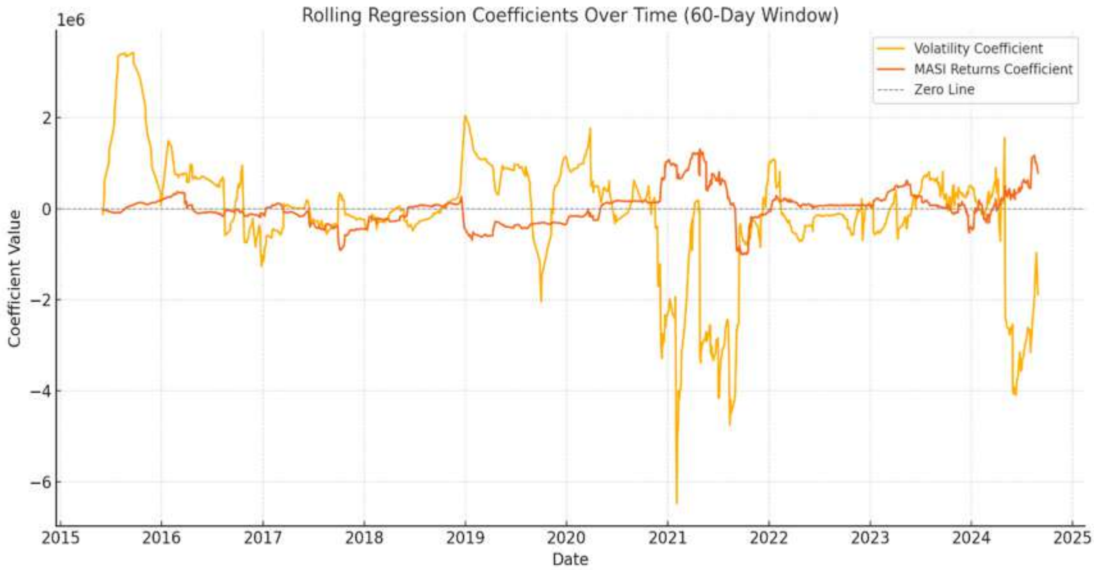
Trading volume also fluctuates widely over time. Some stocks, like Autohall and Total Maroc, see steady trading, suggesting regular investor interest. Others, such as Ennakl and Label Vie, have more sporadic activity, likely due to differences in liquidity, investor attention, or changing market conditions.

Overall, these patterns point to overconfidence as a driver of trading behavior. The next section uses regression analysis to examine how trading volume and market volatility interact, shedding light on how investor sentiment moves the market.

4.1.2 Rolling Regression Analysis: Evolution of Overconfidence Over Time

To capture the dynamic nature of overconfidence, we employ a rolling regression approach using a 60-day window, allowing us to observe fluctuations in key regression coefficients over time. The evolution of volatility (β) and market return (δ) coefficients is presented in Figure 3.

Figure 3: Rolling Regression Coefficients Over Time (60-Day Windo)



This visualization highlights moments of increased overconfidence, especially during times of great market uncertainty. We can see spikes in the volatility coefficient (β) aligning with major market events, showing that investors tend to trade more aggressively when things are unstable. The regression analysis provides some insightful points about overconfidence and trading habits in the Moroccan stock market:

First, there is a clear link between volatility and trading volume in stocks like Label Vie and Total Maroc. Investors tend to trade more when the market is unpredictable, and they often hold an overconfident belief that they can profit from short-term market swings.

Second, past returns have little impact on trading decisions; Moroccan investors do not appear to rely heavily on previous performance, which challenges some typical views of overconfidence.

Finally, overconfidence shifts over time, influenced by changing economic and market conditions. This highlights the need for flexible models to understand investor psychology.

4.2. Herding behavior in Trading Volume

To examine the presence of herding behavior among investors in the Moroccan stock market, we conducted an ordinary least squares (OLS) regression analysis, assessing the relationship between the Cross-Sectional Absolute Deviation of Volume (CSADV) and Market Volume (MV) along with its squared term (MV^2). The results are summarized in Table2.

Table 2: Ordinary Least Squares (OLS) Regression analysis of CSADV and MV

Variable	*Coef.*	*Std Err*	*t-stat*	*p-value*	*Interpretation*
Constant	0.2044	0.057	3.570	0.000	Significant positive baseline dispersion in trading volume.
Market Volume (MV)	4.1556e-05	2.16e-06	19.200	0.000	Strong positive and significant relationship between MV and CSADV. As market volume increases, dispersion also increases.
Market Volume Squared (MV^2)	-1.512e-12	4.69e-12	-0.323	0.747	Not significant. No evidence of non-linearity in the relationship between MV and CSADV (no herding effect).

The coefficient for Market Volume (MV) is positive and highly significant (β = 4.1556e-05, $p < 0.01$). This indicates that as trading volume increases, the spread of individual stock trading activity also increases (Table 2). This finding means that traders do not gather around a typical behavior; instead, they take part in more varied trading as volume rises. On the other hand, the coefficient for Market Volume Squared (MV^2) is negative but not statistically significant (β = -1.512e-12, $p = 0.747$). This provides no evidence of a non-linear relationship between trading volume and dispersion. The lack of significance in MV^2 suggests that herding behavior is weak or not present among Moroccan investors in analyses based on trading volume.

Table 3 presents a summary of regression statistical measures. The estimated R-squared shows a moderate explanatory power, with a value suggesting that about 60.4% of the variation in CSADV is explained by the independent variables. The F-statistic of 798.4 (p-value = 2.14e-211) confirms the overall significance of the model.

Table 3: Summary of Regression Statistical Measures of Herding and Trading Volume

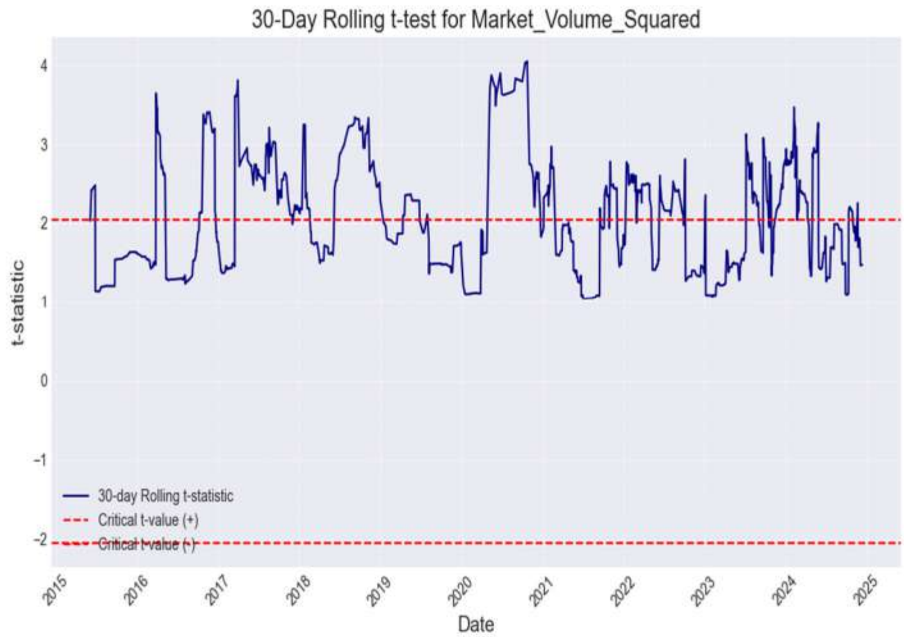
Statistic	**Value**
R-squared	0.604
Adjusted R-squared	0.603
F-statistic (p-value)	798.4 (**p** = 2.14e-211)
Durbin-Watson	1.992
Skewness	14.836
Kurtosis	367.095
Jarque-Bera (JB) Test	5,843,811.516 (**p** < 0.01)

**** Significant at 1%, **Significant at 5% and * Significant at 10%.*

These additional statistical measures further support the strength of the model. The Durbin-Watson statistic (1.992) indicates no strong autocorrelation in the residuals, which confirms the reliability of the estimates. However, the high skewness (14.836) and kurtosis (367.095) show significant deviations from normality. This is further confirmed by the Jarque-Bera test ($p < 0.01$), which rejects the null hypothesis of normality.

To examine the presence or absence of herding behavior, we analyze the relationship between CSAD and Market Volume using both statistical and graphical methods. Figure 4 shows the 30-day rolling t-statistic for the Market Volume Squared (MV^2) coefficient.

Figure 4: The 30-day rolling t-statistic for Market Volume Squared: Time-Varying Analysis in the Retail Trade Sector



The analysis of this figure reveals that the t-statistic consistently stays above -2, which is a positive sign. It suggests there aren't extended periods where the t-statistic dips into the herding zone. This means that if herding effects are present, they tend to be weak and short-lived. This observation aligns well with our regression results. Additionally, the squared term of Market Volume is used to detect non-linearity and to see if dispersion diminishes at higher trading volumes.

From a behavioral finance perspective, this could imply that retail investors in Morocco are less likely to be influenced by panic-driven mass movements. Instead, they probably depend more on fundamental analysis, company-specific information, or independent strategies when making investment decisions.

4.3. Herding behavior in Market Return

4.3.1 Regression Model Results and statistical measures

Table 4 presents the results of the regression analysis. The findings show that Market Return (R_MASI) is not statistically significant ($p = 0.590$). This means that changes in market return do not significantly influence the variation in individual stock returns. More importantly, the coefficient of Market Return Squared (R_MASI²) is positive and highly significant ($p < 0.01$). This suggests that CSAD increases at higher market returns instead of decreasing. This result indicates that investors in the retail trade sector make trades more independently rather than following the overall market trends.

Table 4: Regression Results for Herding in Returns

Variable	Coef	Std Err	t-stat	p-value	Interpretation
Constant	0.0149	0.000	44.457	0.000***	Significant positive baseline dispersion in stock returns.
Market Return (R_MASI)	0.0155	0.029	0.538	0.590 NS	Not significant. No strong relationship between market return and return dispersion.
Market Return Squared (R_MASI^2)	4.4585	0.793	5.625	0.000***	Significant and positive—suggests an increase in return dispersion at higher market returns, contradicting herding behavior expectations.

**** Significant at 1%, **Significant at 5% and * Significant at 10% NS : Non significant*

To further assess the robustness of the regression model, table 5 shows that R-squared value is just 0.031 (and the adjusted R-squared is 0.029), meaning that this model only explains about 3% of the differences in return dispersion (CSAD). This tells us that many other factors beyond market return and its squared term are influencing how returns vary. Even though the F-statistic (16.78, $p < 0.01$) shows a highly significant effect, the variation part explained remain small. Factors like investor mood, company news, or what's happening in specific market sectors probably play a much bigger role in return movement.

Table 5: Statistical Measures for the Regression Model

t-statistic	Value
R-squared	0.031
Adjusted R-squared	0.029
F-statistic (p-value)	16.78 ($p < 0.01$)
Durbin-Watson	1.390
Skewness	1.510
Kurtosis	6.912
Jarque-Bera (JB) Test	1068.289 (**p** < 0.01)

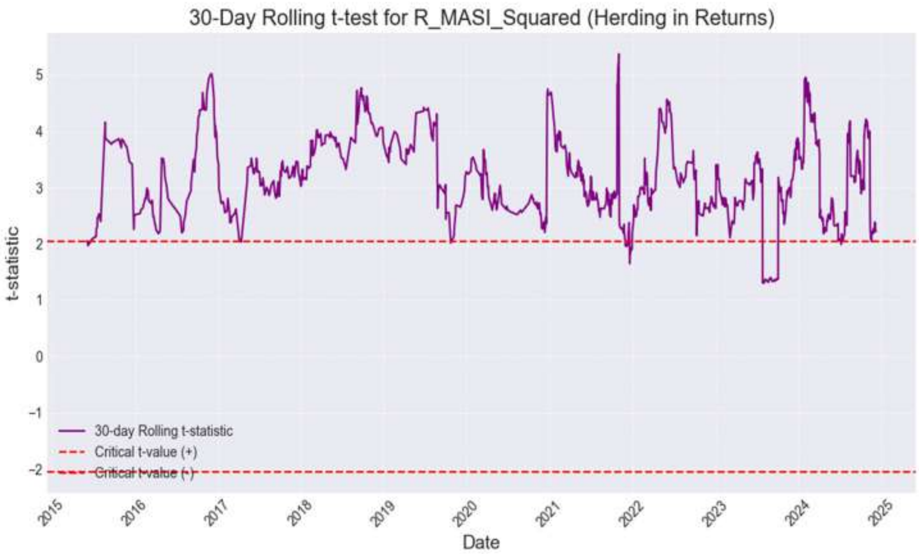
**** Significant at 1%, **Significant at 5% and * Significant at 10%.*

The Durbin-Watson statistic (1.390) shows slight positive autocorrelation, but it is not enough to distort results. The Jarque-Bera test ($p < 0.01$) rejects normality, indicating that the residuals do not behave normally. Furthermore, high kurtosis (6.912) and positive skewness (1.510) suggest that the data may have extreme values. This means that return dispersion can experience occasional spikes instead of following a standard distribution.

4.3.2 Rolling t-Statistic for Market Return Squared: Time-Varying Analysis

Figure 5 shows a 30-day rolling t-statistic for the Market Return Squared (R_MASI^2) coefficient. This helps us evaluate the importance of herding behavior over time.

Figure 5: The 30-Day Rolling t-Statistic for Market Return Squared



Looking at this figure, we can notice that the t-statistic stays mostly above -2, suggesting there aren't any prolonged times where herding is statistically significant. The frequent readings above +2 show that return dispersion tends to increase, which supports the idea that herding isn't occurring. Also, the occasional changes in t-statistics are just brief shifts and don't indicate any sustained herding behavior.

5. Discussion

Our findings reveal that overconfidence significantly influences trading activity in Morocco’s retail trade sector. Excessive trading volumes are particularly evident during periods of positive stock performance or heightened market sentiment. However, this effect is not uniform across all assets—variations in trading volume suggest that factors such as liquidity, volatility, and perceived market opportunities shape the degree of overtrading.

These results align with Sifouh et al. (2017), who demonstrated that overconfident investors on the Casablanca Stock Exchange contribute to market volatility. Similarly, our analysis indicates that increased volatility correlates with heightened trading activity, especially in stocks such as Label Vie and Total Maroc. Lebdaoui et al. (2016) also found that overconfidence positively correlates with increased trading among Moroccan investors. Daniel and Hirshleifer (2015) confirmed that past positive returns amplify investor activity, while Huang et al. (2020) showed that trading diminishes under uncertain conditions. Together, these findings suggest that volatility plays a crucial role in reinforcing overconfidence-driven trading behavior, particularly in fluctuating markets.

Conversely, Benayad and Aasri (2020) found no significant link between overconfidence and investment decisions among Moroccan SME managers. Instead, optimism, risk aversion, and mimicry were more influential. This contrast likely reflects contextual differences: SME managers operate within structured decision-making environments; unlike individual retail investors whose behavior is more affected by market volatility and asset characteristics.

Our study also finds limited evidence of herding behavior among Moroccan investors in the retail trade sector, suggesting that investors tend to trade independently rather than following collective market trends. This result supports Nait Bouzid, Hui, and Fuwei (2020), who observed weak or absent herding in several Moroccan industries, including retail trade. They attributed this to sectoral diversity and differing trading strategies.
Contrary findings, however, exist. El Hami and Hefnaoui (2019) found strong herding in the Moroccan market overall, particularly during volatile periods. Yet, their study did not differentiate by sector, suggesting that herding may vary across industries. Chang, Cheng, and Khorana (2000) also found herding more prevalent in emerging markets due to inefficiencies and sentiment-driven trading.

Recent studies further highlight herding's conditional nature. Borah et al. (2023) reported stronger herding during calm market conditions and low investor attention, while Patwarani and Husodo (2023) found herding in Asian markets mainly during bearish phases. In contrast, Tlili, Chaffai, and Medhioub (2023) identified herding in Morocco during bullish phases, particularly at lower return levels. These mixed findings suggest that herding may emerge under specific market conditions but does not dominate the Moroccan retail trade sector, where trading appears largely independent.

The contrasting evidence across studies underscores the multifaceted nature of overconfidence and herding as behavioral biases. While overconfidence clearly contributes to excessive trading and volatility, its impact varies by investor type and market context. Similarly, herding behavior is not universal but depends on institutional presence, market maturity, and sectoral characteristics.

In the Moroccan retail trade sector, the absence of strong herding and the presence of overconfidence-driven trading suggest a market shaped more by individual decision-making than collective behavior. This may reflect relatively stable sector dynamics, limited speculative trading, and a focus on company fundamentals rather than market sentiment.

In summary, overconfidence shapes behavior in the Moroccan retail trade market, especially in volatile times, while herding is limited. These findings emphasize the need to consider investor type, sector characteristics, and market context. Further research should include other sectors and market phases to build a fuller picture of behavioral patterns in Morocco.

6. Conclusion

This study shows that overconfidence plays a big role in trading behaviors in the Moroccan stock market. It’s clear that many investors tend to trade more than usual, especially when market volatility or recent performance peaks. A strong sign of overconfidence is the positive link between volatility and trading volume, as seen with companies like Label Vie and Total Maroc. These findings suggest that investors often see volatility as an opportunity rather than a threat, which can lead to more aggressive trading and overtrading.

Additionally, some stocks show a positive relationship between past returns and trading activity, supporting the idea that investors expect past winners to keep winning. This pattern reflects overconfidence, where traders believe successful stocks will continue their upward trend, encouraging ongoing speculation.

This analysis also indicates that herding isn’t a major factor in the Moroccan retail sector. Both the regression results and visual checks show that investors tend to make their own decisions rather than follow others’ trading behaviors. This results in more variation in trading volumes when activity is high. Similarly, while examining return dispersion, the analysis suggests that herding isn’t a key driver; instead, return dispersion tends to grow during extreme market swings, which goes against the idea of trend-following behavior.

However, due to the models' limited explanatory power and some non-normal data, it's clear that other factors beyond market returns are influencing return dispersion.

These insights are important for policymakers and investors alike. For regulators, the lack of strong herding indicates a relatively low risk of widespread speculative bubbles driven by irrational trading, whereas for investors, it's reassuring to see that market movements are more rooted in economic fundamentals than collective psychology. However, these conclusions are specific to the retail trade sector considered in this study but might not be for other industries in Morocco's stock market. Herding could still be present in sectors with more speculative activity or different liquidity profiles. Therefore, more detailed sector analyses are needed to get a fuller picture of investor behavior in Morocco. Future research should also look into herding in other sectors, during times of financial stress, or under different macroeconomic conditions to better understand how markets operate across the country.

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