The Impact of Volatility on Herding Behavior: Evidence from Egypt

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Abstract

The study aims to investigate the impact volatility on Herding Behavior in the Egyptian Stock Market. The study used data from companies listed on the Egyptian Stock Exchange. The researcher used a sample of 63 companies daily closing price for ten-year period from 2014 to 2024. The study used a quantitative approach, drawing on secondary data. The results of the study revealed that a significant presence of herding behavior during market upturns. on the other hand, it is insignificant during market downturns. Furthermore, volatility was found to have a significant impact on herding behavior in both rising and falling market conditions.

Keywords: Herding Behavior, Volatility, Egyptian Stock Market, Cross-Sectional Absolute Deviation, Parkinson's volatility, Interest rate, Exchange rate.

الملخص:

تهدف هذه الدراسة إلى التحقيق في تأثير التقلبات على سلوك القطيع في سوق الأوراق المالية المصري. استخدمت الدراسة بيانات من شركات مدرجة في البورصة المصرية، حيث اعتمد الباحث على عينة مكونة من أسعار الإغلاق اليومية لـ ٦٣ شركة خلال فترة عشر سنوات من عام ٢٠١٤ إلى عام ٢٠٢٤. استخدمت الدراسة منهجًا كميًا بالاعتماد على البيانات الثانوية. كشفت نتائج الدراسة عن وجود سلوك قطيع معنوي خلال فترات صعود السوق، بينما لم يكن هذا السلوك ذا دلالة إحصائية خلال فترات الهبوط. علاوة على ذلك، تبين أن للتقلبات تأثيرًا معنويًا على سلوك القطيع في كل من حالات صعود وهبوط السوق.

الكلمات المفتاحية :سلوك القطيع، التقلبات، سوق الأوراق المالية المصري، الانحراف المطلق المقطعي(CSAD) ، تقلبات باركنسون، سعر الفائدة، سعر الصرف.

1. Introduction

Behavioral finance became a recognized field in the early 1980s. Investigating behavioral finance has led to significant results that aid in explaining why financial markets are regularly exposed to irrational behavior, unexpected price fluctuations, and differences from traditional financial theories (Akin & Akin, 2024).

The presence of herding behavior in financial markets requires investigation and documentation for several reasons. Initially, investors and financial managers are cautious regarding the representation of information in stock market valuations. The Efficient market hypothesis states that market participants develop rational expectations regarding future prices through integrating all available market information into their anticipated prices. The presence of herding could increase return volatility, destabilizing financial markets (Demirer & Kutan, 2006).

The role of financial markets and institutions in the economy is crucial, as they serve as the channel for transferring funds from savers to investors. A minor fluctuation in financial asset prices is allowed because of the allocation of funds among competing uses. Excessive market volatility may result in structural or regulatory adjustments (Becketti & Sellon, 1989). Volatility has attracted increasing interest from all financial market participants over the past two decades, leading to the development of forecasting models and explanation of the sources of this variability (Poon & Granger, 2003; Yu, 2002).

According to Komalasari & Asri (2019), investors tend to neglect important private information and instead copy the investing decisions of other investors who they consider to be "informed investors." Their persistent behavior of going with the flow of the market has weakened their ability to make independent decisions. The term "herding" refers to this crowding effect, which is used to explain the trading behavior of investors who irrationally follow market trends

A market's volatility is a representation of its instability and unpredictability (Su et al., 2019). According to research published by Wang & Wang (2018) and Economou et al. (2018), volatility and herding are associated because investors' emotions are driven by fear to herd in the market. However, a different school of thinking believes that there is no connection between herding and volatility. BenSaïda (2017) claims that the volatility of a relatively limited number of certain stocks is impacted by herding. The conflicting findings have raised serious concerns about an association between herding and volatility. Several research that dedicated appreciated attention at relation between herding and volatility have also observed this unclear finding (Mishra & Mishra, 2023).

As herding behavior takes place throughout trading sessions, the herding behavior came to be accepted as an explanation for the excessive market volatility that results in stock price deviations from their fair values. in time of market volatility regardless of (high or low) could lead to herding. The Egyptian stock market is especially prone to herd mentality; to understand and identify the problem of the financial market instability and find better possibilities for improving investment decision investigating herding behavior and Volatility is important As Egyptian market is categorized as an emerging market, exhibiting characteristics such as limited trading activity, illiquidity, a restricted number of listed companies, a scarcity of investment research organizations, and a less rigorous enforcement of corporate governance standards (Ragab et al., 2019). This paper aims to measure the impact of Volatility on Herding Behavior in the Egyptian stock market.

2. Literature Review and Hypothesis Development

In economics and finance, the term herding or herd behavior refers to the phenomenon where economic agents repeat each other's behaviors and/or make judgments influenced by the actions of others (Spyrou, 2013). Herding behavior refers to the tendency of blindly mimicking the choices of others. Furthermore, herding behavior refers to the tendency to follow the crowd in decision-making, even when the group's choices are incorrect (H. Wang et al., 2018).

Herding is classified into two categories: Spurious herding and intentional herding (Caparrelli et al., 2004). All investors making the same decision due to the same information is spurious herding. Market analysis and personal opinions influence their actions. Since actions are informed decisions, this category of herding tends not to affect the market. However, intentional herding is pure imitation of others, regardless of charges. It occurs when investors follow other market players against their own judgment because they question their decision-making process, view other investors as superior, or desire conformity. This form of herding concerns us because it may affect the market. Herding depends on personality and context.

Herding behavior has been observed in international stock markets, including those of China (Wu et al., 2020), Malaysia (Loang & Ahmad, 2022; Muharam et al., 2021), the USA (Duygun et al., 2021), and Australia (Espinosa-Méndez & Arias, 2021). Yao et al. (2014)investigate the presence and frequency of herding behavior in the Chinese A and B stock markets. The findings indicate that herding occurs at various levels of the market under both upward and downward scenarios, with a more pronounced herding tendency in B-share markets.

$\boldsymbol{H_1}$: There is significant herding behavior though market up situation.

$\boldsymbol{H_2}$: There is significant herding behavior though market down situation.

According to Merton (1980), volatility has been primarily regarded as a measuring of risk in financial markets. Various schools of thought emerge about the interpretation of volatility. Zhang et al. (2020) characterized volatility as an expression of fear among market participants. According to Seth & Singhania (2019), volatility can also be defined as changes in the price of underlying assets that are traded in various financial markets. As new information becomes available, the market's volatility shifts (Ross, 1989).

Typically, researchers employ two primary methodologies to assess volatility. The initial approach is to obtain insights on the variance of future returns from historical data through the use of Sample models, Exponentially Weighted Moving Average models, Autoregressive Conditional Heteroscedastic models, Stochastic volatility models, or Realized volatility. The alternative strategy involves deriving market anticipations of future volatility from observed option prices through the utilization of implied volatility indices (Kambouroudis et al., 2016).

In reality, volatility is influenced by multiple factors, such as macroeconomic announcements, political occurrences, earnings disclosures, interest rate fluctuations, and worldwide emergencies(Kamal & Mahfouz, 2021). Furthermore, volatility has a key role in influencing investment behavior. According to behavioral finance theories as Prospect Theory (Kahneman & Tversky, 1979), investors are not always rational and are more sensitive to losses than gains. In highly volatile circumstances, loss aversion drives investors to make emotionally driven actions, such as panic selling or blindly adhering to others. This behavior referred as herding.

Although herding is a widespread phenomenon in markets, only a limited amount of research take volatility into consideration as a possible contributing factor. Economou et al. (2018) investigate the relationship between investor's fear and herding behavior, indicating that volatility serves as a trigger for fear, potentially leading to herding. They propose that volatility pushes investors to adhere to collective trading behaviors. This claim has been confirmed by the empirical findings of Bekiros et al. (2017) examine the influence of market sentiment on herding and indicate that market volatility could enhance the herding a tendency through a positive linear correlation. These findings indicate that volatility could be serving as a major trigger for herding behavior. This study is motivated by existing research to further investigate the function of volatility in causing herding and to provide additional empirical evidence supporting this relation.

$\boldsymbol{H_3}$: There is a significant impact from volatility on herding behavior though market up situation.

$\boldsymbol{H_4}$: There is a significant impact from volatility on herding behavior though market down situation.

3. Research Design and Methodology

The sample period starts from January 2014 to December 2024. The timeframe for the sample provides an extended and reliable framework to analyze the impact of volatility on herding behavior in the Egyptian stock market.

This research relies on a comprehensive ten years of daily data to analyze investor behavior (herding) under varying market conditions, The study examines how this relation changes throughout Bull and Bear market conditions.

The research employs the well-established model known as the Cross-Sectional Absolute Deviation (CSAD). This model helps with determining whether investors are aligning in the same direction, especially during significant market fluctuations. Furthermore, quantile regression is employed to analyze the variability of herding behavior over time. Volatility is measured by Parkinson's volatility. Control variables are Exchange rate and interest rate. The approach involves using Ordinary Least Squares (OLS) regression to assess the impact of volatility on herding behavior in both bullish and bearish markets.

4. Modeling

4.1 Modeling Herding

Cross-sectional absolute deviation (CSAD) is one of the most widely used metrics for herding measurements (Chang et al., 2000). To study how investors follow the market return, CSAD calculates the dispersion between the stock return and the market return. If the dispersion decreases because of the smaller group of investors making identical investment decisions to a bigger group of investors, then this is valid proof of herding. To address

CSSD's oversensitivity to outliers, Chiang & Zheng (2010) modified the cross-sectional standard deviation (CSSD), as suggested by Christie & Huang (1995), to CSAD. The CSAD formula is represented below:

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

Whereas N is the number of stocks, $R_{i,t}$ is the observed stock return of stock i at time t, $R_{m,t}$ is the market return and CSAD stands for cross-sectional absolute deviation of stock i at time t.

To identify if herding is occurring, the CSAD regression is extended to include the following variables:

$$CSAD_{i,t} = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2\left|R_{m,t}\right| + \gamma_3 R^2{}_{m,t} + \varepsilon_t$$

Whereas $R^2{}_{m,t}$ denotes the squared equally weighted cross-sectional average return for the index on day t, $\left|R_{m,t}\right|$denotes the absolute value of $R_{m,t}$.

Quantile regression, on the other hand, calculates the conditional median across a range of values (Porter, 2015). According to Chiang et al. (2010), the linear regression CSAD approach has a tendency not to include data regarding a distribution's tails.

This study uses the following equation from Economou et al. (2018) to investigate the presence of herding in market up (bullish) and down (bearish) conditions:

- Bull Market

$$CSAD_{it}^{Up} = \beta_0 + \beta_2^{Up} R_{m,t}^{Up} + \beta_2^{Up} \left|R_{m,t}^{Up}\right| + \beta_3^{Up} R_{m,t}^{Up^{\,2}} + \varepsilon_t$$

- Bear Market

$$CSAD_{it}^{Down} = \beta_0 + \beta_2^{Down} R_{m,t}^{Down} + \beta_2^{Down} \left|R_{m,t}^{Down}\right| + \beta_3^{Down} R_{m,t}^{Down^2} + \varepsilon_t$$

4.2 Modeling Volatility

Parkinson's volatility is derived from the study of Parkinson (1980) to evaluate volatility using the daily maximum and minimum prices. The data is different from realized volatility. When measuring volatility, Parkinson's volatility is more detailed than realized volatility. The following is the Parkinson's volatility the following formula:

$$\sigma_P = \frac{1}{2\sqrt{In2}} \sqrt{\frac{1}{n} \sum_{t=1}^{n} P^2{}_{i,t}}$$

where $P_{i,t} = In \frac{H_{i,t}}{L_{i,t}}$ and $H_{i,t}$ is the maximum price of stock i at time t and $L_{i,t}$ is the minimum price of stock i at time t. Parkinson's volatility emphasizes the mobility of stock prices from an intraday perspective while realized volatility focuses on using the dispersion of ending stock prices. The use of maximum and minimum prices in Parkinson's volatility facilitates extreme volatility and enables forecasting.

5. Results and Discussion

The study population consists of all firms registered under EGX 100 and being under the index from January 2014 till December 2024 on a daily basis. The researcher succussed in collecting a data from 63 firms on a daily basis though out the time period of study, by which she collected data for the 63 firms reached to 2677 observations, and she found that 1334 observations out of the 2677 have a situation of market up, while there are 1339 observations have situation of market down and there are 4 observations have neither market up nor down situation and excluded from the sample.

5.1Detecting the herding behavior though the study sample:

In order to detect the herding behavior and testing the first and second hypotheses through the study sample which consists of 2673 observations, the researcher will divide them according to the market situation to be either up or down and apply a quantile regression and check the significance and the direction of β_3^{Up} and β_3^{Down} in order to detect the herding behavior.

5.1.1 Detecting the herding behavior though market up situation:

The researcher will apply a quantile regression model to the Cross Section Absolute Deviation (CSAD) Econometric model in case of an up situation and the results obtained in the following table (1).

Table (1): Quantile Regression model for CSAD though market up

Model	*Q. Regression*	**Dependent variable**		CSAD-up	**Significance**
Independent variables	**tau**	**coefficient**	**std. error**	**t-ratio**	
Constant	10%	0.00815056	0.000141454	57.6199	***
	20%	0.00937946	0.000162872	57.588	***
	30%	0.0102361	0.000151416	67.6021	***
	40%	0.0110717	0.000172352	64.2391	***
	50%	0.0119582	0.000221289	54.0391	***
	60%	0.0126429	0.000196378	64.3803	***
	70%	0.01359	0.000227064	59.8507	***
	80%	0.0150639	0.000301725	49.9259	***
	90%	0.0173041	0.000341849	50.6192	***
Market Return	10%	0.0192965	0.00760525	2.53727	***
	20%	0.0381397	0.00875677	4.35546	***
	30%	0.0463808	0.00814087	5.69728	***
	40%	0.0523403	0.00926646	5.64836	***
	50%	0.0446048	0.0118975	3.74908	***
	60%	0.0415103	0.0105582	3.93156	***
	70%	0.0426166	0.0122081	3.49086	***
	80%	0.0409431	0.0162222	2.52389	***
	90%	0.0917831	0.0183794	4.99379	***
Absolute Market Return	10%	0.295931	0.0202215	14.6344	***
	20%	0.243993	0.0232833	10.4793	***
	30%	0.229804	0.0216457	10.6166	***

	40%	0.210416	0.0246385	8.54011	***
	50%	0.215889	0.0316343	6.82453	***
	60%	0.230216	0.0280732	8.20055	***
	70%	0.209185	0.0324599	6.44441	***
	80%	0.162619	0.0431331	3.77017	***
	90%	0.120964	0.048869	2.47527	***
Market Return Squared	10%	-1.82294	0.478518	-3.80955	***
	20%	-0.692486	0.550971	-1.25685	*
	30%	0.334775	0.512219	0.653579	Insignificant
	40%	0.514315	0.58304	0.882126	Insignificant
	50%	0.252784	0.748586	0.337682	Insignificant
	60%	0.195248	0.664317	0.293908	Insignificant
	70%	1.74798	0.768123	2.27565	**
	80%	2.86634	1.02069	2.80823	***
	90%	3.79411	1.15642	3.2809	***
F-test	135.2748	***p-value***		1.65e-76	
Adjusted R-squared			23.1665%		

Source: prepared by the researcher from Gretl output

*****: Significant at 1%.**

****: Significant at 5%.**

***: Significant at 10%.**

From table (1) it is concluded that the quantile regression results for "Market Return Squared" show that moments in an "up market" when herding behavior is relatively subdued, strong positive market returns appear to act as a diversifying force, leading to a reduction in herding among market participants.

<u>Negative and Significant at Lower Quantiles (10% and 20%):</u>

- At the 10th percentile (tau = 0.100), the coefficient for Market Return Squared is -1.82294, with a t-ratio of -

3.80955, indicating high statistical significance (typically at the 1% level).

- At the 20th percentile (tau = 0.200), the coefficient is -0.692486, with a t-ratio of -1.25685, which is significant (typically at the 10% level).

5.1.2 Detecting the herding behavior though market down situation:

The researcher will apply a quantile regression model to the Cross Section Absolute Deviation (CSAD) Econometric model in case of down situation, and the results obtained in the following table (2).

Table (2): Quantile Regression model for CSAD though market down

Model	*Q. Regression*	**Dependent variable**		CSAD-down	**Significance**
Independent variables	**tau**	**coefficient**	**std. error**	**t-ratio**	
Constant	10%	0.00972384	0.000183424	53.0129	***
	20%	0.0110518	0.000185761	59.4945	***
	30%	0.0120769	0.000232542	51.9343	***
	40%	0.0131963	0.000273083	48.3234	***
	50%	0.0144942	0.000215488	67.2621	***
	60%	0.0153007	0.000246597	62.0474	***
	70%	0.0166655	0.000348125	47.8722	***
	80%	0.0179432	0.000317609	56.4948	***
	90%	0.0203443	0.000570215	35.6783	***
Market Return	10%	0.023038	0.00605302	3.80603	***
	20%	0.0346326	0.00613013	5.64957	***
	30%	0.0317775	0.00767393	4.14097	***
	40%	0.0341336	0.00901178	3.78766	***

	50%	0.0434796	0.00711113	6.1143	***
	60%	0.0508331	0.00813774	6.24659	***
	70%	0.0545283	0.0114882	4.74647	***
	80%	0.0811695	0.0104811	7.74434	***
	90%	0.103926	0.0188172	5.52294	***
Absolute Market Return	10%	0.205682	0.019636	10.4747	***
	20%	0.18769	0.0198862	9.43821	***
	30%	0.159517	0.0248943	6.40779	***
	40%	0.123698	0.0292343	4.23126	***
	50%	0.075942	0.0230685	3.29202	***
	60%	0.0737184	0.0263989	2.79248	***
	70%	0.0708706	0.0372677	1.90166	*
	80%	0.049996	0.0340008	1.47043	*
	90%	0.0479447	0.0610429	0.785425	Insignificant
Market Return Squared	10%	-0.288438	0.374154	-0.770907	Insignificant
	20%	0.23212	0.378921	0.612582	*
	30%	0.952944	0.474347	2.00896	**
	40%	1.94466	0.557044	3.49104	***
	50%	3.04451	0.439559	6.92629	***
	60%	3.48727	0.503017	6.93272	***
	70%	3.55926	0.710116	5.01222	**
	80%	4.56348	0.647868	7.04385	***
	90%	4.97481	1.16314	4.27705	***
F-test	135.2748	***p-value***		1.65e-76	
Adjusted R-squared			23.1665%		

Source: prepared by the researcher from Gretl output

*****: Significant at 1%.**

****: Significant at 5%.**

***: Significant at 10%.**

<u>From table (2) it is concluded that:</u>

- At the 10th percentile (tau = 0.100): The coefficient is -0.288438. However, its t-ratio is -0.770907, which means that herding behavior is existing but not significant, by which herding behavior cannot be generalized to the overall population of study, it's stated regarding this sample only.

- For all other quantiles (20% through 90%): The coefficients for "Market Return Squared" are positive and, for most of these quantiles (20% onwards, with high significance from 30% to 90%).

5.2 Analysis of study variables in case of market up:

5.2.1 Market-up variables' descriptive analysis:

The market- up variables will be analyzed in order to determine measures of central tendency which are presented by (arithmetic mean, maximum and minimum values), then measures of dispersion which are presented by (standard deviation and coefficient of variation) for each variable.

Table (3): The descriptive analysis of market up variables.

Variable	Minimum	Maximum	Mean	Standard Deviation	Coefficient of Variation
CSAD	0.006	0.035	0.014	0.004	0.279
Volatility	0.019	0.159	0.044	0.031	0.710
Exchange rate	6.956	51.030	18.586	10.780	0.580
Interest rate	0.083	0.277	0.141	0.053	0.379

Source: prepared by the researcher from SPSS output.

From table (3) it is concluded that The Cross-Sectional Absolute Deviation (CSAD) exhibits a low level of dispersion, with values ranging from 0.006 to 0.035, a mean of 0.014, a standard deviation of 0.04, and a coefficient of variation of 27.9%. Similarly, the Interest Rate variable also shows low dispersion, with a range of 0.083 to 0.277, a mean of 0.141, a standard deviation of 0.053, and a coefficient of variation of 37.9%. In contrast, both Volatility and Exchange Rate variables demonstrate moderate levels of dispersion. Volatility has a range from 0.019 to 0.159, a mean of 0.044, a standard deviation of 0.031, and a coefficient of variation of 71%. The Exchange Rate, with values spanning from 6.956 to 51.030, has a mean of 18.586, a standard deviation of 10.780, and a coefficient of variation of 58%. In all cases, the standard deviation is less than 1, reinforcing the respective levels of dispersion around their arithmetic means.

5.2.2 Market-up variables' Correlation Matrix:

After applying the test of normality for the study variables and finding them don't follow the normal distribution, Spearman correlation coefficient will be the most appropriate coefficient for determining the relation strength and direction between each two variables, then the correlation coefficient is tested by a t-test which its null hypothesis states that correlation does not exist if the test *p-value* is greater than 0.05.

Table (4): Spearman correlation coefficient for market up

Variable	CSAD	Volatility	ER	IR
CSAD	**1**			
P-value	-			
Volatility	0.294**	**1**		
P-value	*0.000*	-		
ER	0.317**	0.924**	**1**	
P-value	*0.039*	*0.000*	-	
IR	0.185**	0.860**	0.880**	**1**
P-value	*0.000*	*0.000*	*0.000*	-

Source: prepared by the researcher from SPSS output.

From table (4) it is concluded that the analysis of correlations between the variables reveals several significant relationships, all with a p-value of 0.000, indicating statistical significance. A direct, weak, and significant relationship is observed between Cross-Sectional Absolute Deviation (CSAD) and Volatility (VOL), with a correlation coefficient of 0.294. Similarly, CSAD shows a direct, weak, and significant relationship with Exchange Rate (ER), with a correlation coefficient of 0.317, and with Interest Rate (IR), with a correlation coefficient of 0.185. In contrast, stronger direct and significant relationships are found among the remaining pairs: Volatility (VOL) and Exchange Rate (ER) exhibit a robust correlation of 0.924, while Volatility (VOL) and Interest Rate (IR) show a strong correlation of 0.860. Finally, a strong direct and significant relationship also exists between Interest Rate (IR) and Exchange Rate (ER), with a correlation coefficient of 0.880. These results suggest that while CSAD has a weaker linear association with the other variables, Volatility, Exchange Rate, and Interest Rate are highly inter-correlated.

5.3 Testing the study third hypothesis H_3:

The third hypothesis of the study states that: "there is a significant impact from volatility on herding behavior though market up situation.", the researcher will develop a multiple linear ordinary least squares (OLS) regression models to test the impact of volatility (independent variable) on CSAD (dependent variable).

Table (5): Multiple regression model for the third hypothesis H_3

Model	*OLS multiple*	**Dependent variable**	CSAD	**VIF**
Variables	***Coefficient***	***p-value***	**Significance**	
Constant	0.0141657	<0.0001	**Significant**	
Volatility	0.0191810	0.0299	**Significant**	7.217
Exchange rate	0.000210389	<0.0001	**Significant**	8.320
Interest rate	−0.0331941	<0.0001	**Significant**	4.689
F-test	73.67454	***P-value***	4.32e-44	
Adjusted R-squared	14.0296%			

Source: prepared by the researcher from SPSS output

From table (5) it is concluded that:

- The overall multiple (OLS) regression model is significant as it has F-test of 73.67454 with *p-value* less than 0.05, with an adjusted R-squared value 14.0296% which means that the dependent variable CSAD changes by 14.0296% due to the changes in (volatility, exchange rate and interest rate).
- Constant volatility and exchange rates have a direct and significant impact on CSAD.
- Interest rate has an inverse and significant impact on CSAD.
- The AI technology dimensions don’t suffer from problems of multi-collinearity as variance inflation factor (VIF) test showed results less than 10.

The (OLS) regression model forecasting equation will be:

$$\widehat{CSAD}_{it} = 0.0141657 + 0.0191810\ \mathrm{VOL_{it}} + 0.000210389\ \mathrm{ER_{it}} - 0.0331941\ \mathrm{IR_{it}}$$

5.4 Analysis of study variables in case of market down:

5.4.1 Market-down variables’ descriptive analysis:

The market- down variables will be analyzed in order to determine measures of central tendency which are presented by (arithmetic mean, maximum and minimum values), then measures of dispersion which are presented by (standard deviation and coefficient of variation) for each variable.

Table (6): The descriptive analysis of market-down variables.

Variable	Minimum	Maximum	Mean	Standard Deviation	Coefficient of Variation
CSAD	0.008	0.060	0.017	0.005	0.305
Volatility	0.019	0.155	0.043	0.030	0.705
Exchange rate	6.958	50.870	18.418	10.655	0.578
Interest rate	0.083	0.276	0.140	0.053	0.377

Source: prepared by the researcher from SPSS output.

From table (6) it is concluded that the Cross-Sectional Absolute Deviation (CSAD) variable displays a low level of dispersion, with values ranging from 0.008 to 0.060, an arithmetic mean of 0.017, a standard deviation of 0.05, and a coefficient of variation of 30.5%. Similarly, the Interest Rate variable also exhibits low dispersion, with a minimum of 0.083, a maximum of 0.276, a mean of 0.140, a standard deviation of 0.053, and a coefficient of variation of 37.7%. In contrast, both the Volatility and Exchange Rate variables show moderate levels of dispersion. Volatility ranges from 0.019 to 0.155, with a mean of 0.043, a standard deviation of 0.030, and a coefficient of variation of 70.5%. The Exchange Rate variable spans from 6.958 to 50.870, with a mean of 18.418, a standard deviation of 10.655, and a coefficient of variation of 57.85%. For all variables, the standard deviation is less than 1, reinforcing the stated levels of dispersion around their respective arithmetic means.

5.4.2 Market-down variables' Correlation Matrix:

After applying the test of normality for the study variables and finding them don't follow the normal distribution, Spearman correlation coefficient will be the most appropriate coefficient for determining the relation strength and direction between each two variables, then the correlation coefficient is tested by a t-test which its null hypothesis states that correlation does not exist if the test *p-value* is greater than 0.05.

Table (7): Spearman correlation coefficient for market down

Variable	CSAD	Volatility	ER	IR
CSAD	**1**			
P-value	-			
Volatility	0.268**	**1**		
P-value	*0.000*	-		
ER	0.290**	0.923**	**1**	
P-value	*0.039*	*0.000*	-	
IR	0.145**	0.859**	0.878**	**1**
P-value	*0.000*	*0.000*	*0.000*	-

Source: prepared by the researcher from SPSS output.

From table (7) it is concluded that the correlation analysis reveals several statistically significant relationships among the variables, all exhibiting a p-value of 0.000. Specifically, Cross-Sectional Absolute Deviation (CSAD) demonstrates direct, weak, and significant relationships with Volatility (VOL) (correlation coefficient = 0.268), Exchange Rate (ER) (correlation coefficient = 0.290), and Interest Rate (IR) (correlation coefficient = 0.145). In contrast, the relationships among the other variables are notably stronger. There is a direct, strong, and significant correlation between Volatility (VOL) and Exchange Rate (ER) (correlation coefficient = 0.923). Similarly, Volatility (VOL) and Interest Rate (IR) also share a direct, strong, and significant relationship (correlation coefficient = 0.859). Lastly, a direct, strong, and significant relationship is observed between Interest Rate (IR) and Exchange Rate (ER) (correlation coefficient = 0.878). These findings suggest that while CSAD has a more modest linear association with the other factors, Volatility, Exchange Rate, and Interest Rate are highly and positively inter-correlated.

5.5.3 Testing the study fourth hypothesis H_4:

The fourth hypothesis of the study states that: “there is a significant impact from volatility on herding behavior though market down situation.”, the researcher will develop a multiple linear ordinary least squares (OLS) regression models to test the impact of volatility (independent variable) on CSAD (dependent variable).

Table (8): Multiple regression model for the fourth hypothesis H_4

Model	*OLS multiple*	**Dependent variable**	CSAD	**VIF**
Variables	***Coefficient***	***p-value***	**Significance**	
Constant	0.0176785	<0.0001	**Significant**	
Volatility	0.0288791	0.0135	**Significant**	7.229
Exchange rate	0.000287105	<0.0001	**Significant**	8.284
Interest rate	−0.0508664	<0.0001	**Significant**	4.688
F-test	72.96191	***P-value***	1.07e-43	
Adjusted R-squared	13.8933%			

Source: prepared by the researcher from SPSS output

<u>From table (4.11) it is concluded that:</u>

- The overall multiple (OLS) regression model is significant as it has F-test of 72.96191 with *p-value* less than 0.05, with and adjusted R-squared value 13.8933% which means that the dependent variable CSAD changes by 13.8933% due to the changes in (volatility, exchange rate and interest rate).
- Constant volatility and exchange rates have a direct and significant impact on CSAD.
- Interest rate has an inverse and significant impact on CSAD.
- The AI technology dimensions don’t suffer from problems of multi-collinearity as variance inflation factor (VIF) test showed results less than 10.

The (OLS) regression model forecasting equation will be:

$\widehat{CSAD}_{it} = 0.0176785 + 0.0288791\ \mathrm{VOL}_{it} + 0.000287105\ \mathrm{ER}_{it} - 0.0508664\ \mathrm{IR}_{it}$

6. Conclusion

This research investigated the impact of Volatility on Herding behaviour. The study used a sample that consists of 63 Egyptian companies that are listed on the Egyptian stock exchange for ten years from the year of 2014 and 2024. The study empirical findings indicate that Herding was found to be more pronounced during market up particularly in the initial years of the sample where investors tend to follow the crowd when the market is up.

On the other hand, herding behavior during market down was weak and statistically insignificant. This indicate that investors act more cautiously when the market is falling, either relying more on their own judgment or feeling uncertain about which direction to follow.

Furthermore, the analysis also showed that volatility has a significant and positive impact on herding behavior. Consequently, when price fluctuations and the uncertainty in the market increase, investors tend to imitate others instead of rely on their own information.

The study finally shows that volatility significantly impacts herding behavior during market downturns. This illustrates standard risk aversion, as in times of significant uncertainty and market volatility, investors often imitate others and sell to prevent further losses. This causes an ongoing pattern of selling pressure and increases the undesirable occurrences on prices.

7. Research Limitations

The research has several limitations that could be presented as follow:

- The study focuses only on the Egyptian stock market, which may limit the generalize the findings to other emerging or developed markets.
- The analysis is based only on one measure of herding behavior (CSAD) and one measure of volatility (Parkinson), which might not capture all aspects of investor behavior or market dynamics.
- Lastly, high-frequency data (e.g., hourly or minute-by-minute) was not available, which could have provided a more detailed view of herding during volatile periods.

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