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HERDING BEHAVIOR AND STOCK MARKET EFFICIENCY: AN EMPIRICAL STUDY IN THE EGYPTIAN STOCK MARKET

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Abstract: This paper examines the impact of herding behavior on market efficiency in the Egyptian stock market. It does so by testing the efficiency of two separate stock portfolios: one that exhibits statistically significant herding, and another in which herding is not significant. The efficiency was tested using the Runs test and the Augmented Dickey-Fuller test for Unit Root. Hwang and Salmon (2004) methodology was also applied to measure herding behavior. Our comprehensive analysis revealed several key findings regarding market efficiency at the weak form. Firstly, Shapiro-Wilk and Kolmogorov-Smirnov tests indicated that stock prices for both portfolios are not normally distributed, suggesting a deviation from the assumptions of weak-form efficiency. Secondly, the Runs test conclusively showed that the time series for both portfolios are non-random, further demonstrating the market's inability to achieve a weak level of efficiency. Finally, the Augmented Dickey-Fuller (ADF) test confirmed the stationarity of the return series for both portfolios, unequivocally rejecting the presence of a unit root and reinforcing the conclusion of market inefficiency at the weak level. Collectively, these results strongly reject the random walk hypothesis and demonstrate that the Egyptian stock market does not achieve weak-form efficiency, regardless of the presence or absence of herding behavior. This finding has significant implications for investors: it suggests that investors may be able to exploit past price information to potentially generate abnormal returns, as market prices do not fully reflect all available historical data.

Introduction

The debate between financial market efficiency and behavioral finance has been a topic of controversy for decades. While the theory of market efficiency argues that investors act rationally and that stock prices rapidly adjust to reflect all available information, behavioral finance challenges this notion. It explores the influence of psychology on investor behavior, suggesting that markets are not always rational and that investors often make irrational decisions, leading to potential mispricing of assets.

In the 1960s and early 1970s, there was disagreement over whether stock prices followed random movement or not. The tests by Fama (1965) and Samuelson (1965a) were conducted to answer this question; they concluded that most of the evidence appeared to be consistent with the market efficiency hypothesis. The stock market is considered efficient when it is efficient to process information, as Fama (1976) suggests. In an efficient stock market, stock prices fully incorporate all available information; therefore, no investor can achieve abnormal returns through past stock prices or private sources.

Regarding herding behavior, Hwang and Salmon (2004) explained that it occurs when investors choose to follow others' decisions in the market instead of relying on their own beliefs and information. In such cases, investors disregard their own insights in favor of imitating others, regardless of whether the behavior is rational. Herding behavior is also a phenomenon that occurs during periods of stress. When significant price changes occur, individual investment returns align with the market. In the presence of herding behavior, all investments follow the same trajectory as the market portfolio. As a result, investors engaging in herding behavior cause these returns to converge with the market return, thereby reducing their deviation from it.

Through this study, we are trying to identify the impact of herding behavior on the efficiency of the Egyptian stock market by analyzing the efficiency of a portfolio of stocks showing herd behavior among investors and the efficiency of a portfolio of stocks that does not show herding behavior.

Theoretical Background And Previous Studies

Financial Market Efficiency

The market efficiency hypothesis is based on the "random walk theory" for both Kendall (1953) and Fama (1965), which is used to characterize the stock price chain, where each subsequent price change is random and independent of previous prices. The "random walk theory" suggests that when information flows freely and is instantly incorporated into stock prices, tomorrow's price changes will solely reflect new information from that day, independent of today's price movements. Consequently, stock prices are unpredictable, meaning price changes occur randomly and unexpectedly. As a result, all new information is fully reflected in prices, ensuring that even uninformed investors can achieve high returns similar to experts. Cootner (1964) also stated that the stock market does not retain any memory, as the way the stock price behaves in the past does not help determine its future behavior. Samuelson (1965b) also indicated that with respect to the "random walk theory", there were no patterns that investors could employ to achieve abnormal returns; if any excess returns are achieved, they should be credited to luck or seen as compensation for the additional risks taken by the investor. In other words, outperforming the market is not possible.

Fama (1970) noted that all the information that can be gathered concerning the stock has already been incorporated into the stock price, where stock prices reflect all the stock's information. Fama (1970) used the term "efficient market". According to the term "efficient market", competition will instantly counteract the full impact of new information on actual prices. Financial market efficiency levels are three, with Fama (1970) classifying them as weak, semi-strong, and strong.

The assumption of a lower-level efficient stock market suggests that current stock prices fully incorporate all available historical price information, making past prices ineffective for predicting future price movements; therefore, no investor can achieve abnormal returns through previous stock prices. The semi-strong form of financial market efficiency is a model in which current stock prices incorporate all publicly available information, including economic factors, financial reports of the firm and other publicly available information in addition to previous stock prices. Finally, the strong form of efficiency assumes that stock prices fully incorporate all available information, both public and private, preventing any investor from gaining abnormal returns through private insights.

Shiller (1999) noted that although the theory of financial market efficiency remains the basis for the development of many tools and models used to understand how financial markets operate, it failed to explain investors' behaviors. Yao, Ma and He (2014) find that the theory of financial market efficiency failed to learn the mechanisms for the functioning of financial markets due to cognitive biases and complex human responses.

In the early 1960s and mid-1970s, the concept of market efficiency was broadly embraced by academic financial economists, as evidenced by works such as Fama (1970), Fama and MacBeth (1973), Black, Jensen and Scholes (1972), and Jensen (1978). There was a general belief that stock markets were highly efficient in their ability to reflect stock information at the individual or the stock market level as a whole. Meanwhile, Fama, Fisher, Jensen and Roll (1969) found that in an active market involving many knowledgeable and intelligent investors, stock prices will accurately reflect all available information.

Rationality is one of the fundamental pillars of the classical theory of finance, where Barberis and Thaler (2003) indicate that when new information reaches the market, investors make decisions based on Baez's law, aligning their choices with their expected personal benefit, since, under conditions of uncertainty, they choose the decision that delivers the greatest expected self-benefit.

After the mid-1970s, an increase in research challenged the assumption of market efficiency. More specifically, numerous researchers observed that stock prices exhibited certain unexplained patterns that could not be accounted for by the asset pricing models of the time. These patterns, known as "anomalies", posed a significant challenge for emerging markets, as they could not be predicted by existing asset pricing models. Anomalies sparked extensive research that challenged the assumption of investor rationality, a fundamental principle of stock market efficiency. This led many researchers to explore what later became known as behavioral finance, drawing on cognitive psychology to argue that human behavior is not always rational. Studies have documented various behavioral and cognitive biases that influence decision-making and deviate from logical judgments. These findings present a significant challenge to market efficiency, suggesting that markets are not entirely homogeneous, and investors are not always fully rational, as documented by Rozeff and Kinney (1976), French (1980), and Shiller (1999).

There are several other applied studies that have explored market efficiency. Ozkan (2021) aimed to investigate the impact of the recent coronavirus (COVID-19) pandemic on stock market efficiency for six hard-hit developed countries. The study's population and sample included daily stock market data from the United States (US), Spain, the United Kingdom (UK), Italy, France, and Germany. The time period of the analysis spanned from July 29, 2019, to January 25, 2021. To measure market efficiency. The key finding indicated that all stock markets examined deviated from market efficiency during some periods of the pandemic, with deviations being more pronounced in the US and UK stock markets during the outbreak. This suggests an increasing chance for stock price predictions and abnormal returns during the COVID-19 pandemic.

El Mosallamy and Gamal (2024) focused on the Egyptian stock market, specifically analyzing data from the EGX30 and EGX100 indices, with the primary goal of investigating the impact of currency devaluation events on the market's efficiency. Their study's time period covered the significant devaluation events in Egypt during 2016 and 2022. To measure efficiency, they employed both parametric and non-parametric unit root tests for stationarity, along with ARCH and EGARCH models. The key finding indicated that the Egyptian market's returns showed stationarity regardless of these major economic events, suggesting a certain level of efficiency even amidst such turbulence.

Herding Behavior in Financial Markets

In the late 19th century, psychologist and sociologist Gustave Le Bon (1895) explored crowd psychology and drew intriguing conclusions about how individuals behave when they become part of a crowd; these include the absence of responsibility and infection. The absence of responsibility means that when an individual joins a crowd, their sense of responsibility that governs behavior diminishes, and thus the individual carries out actions that he would not have chosen without his presence in the crowd. Infection means that when part of the crowd, the individual disregards their personal beliefs and interests, conforming instead to the beliefs of the crowd; thus, individuals change attitudes and often behave very differently from their basic behavior in the crowd or group than if they acted individually.

Both Bikhchandani and Sharma (2001) defined herding behavior as inadvertently or intentionally copying the behavior of other investors by some investors. Hirshleifer and Teoh (2003) have noted that herding behavior involves similar behavior, and the causes of this similarity cannot always be deciphered, as it can be attributed to a variety of motivations with both psychological and rational backgrounds. Hirshleifer (2001) noted that "conformity" is one of the most important factors related to psychological background in which people feel more comfortable matching the work that others do, If an investment method has been successful in the past and is widely adopted by investors, it is likely that others will follow the same approach, selecting stocks based on the characteristics outlined by that method. Thus, maintaining the same pattern will lead to herding behavior. Devenow and Welch (1996) explained that investors considered it logical to mimic others if this would allow them to benefit from other person's accumulated potential information experiences. The reason for this is that the investor may not have any information or may have information but is unsure of its decisions, perhaps because the investor's information is of low quality, considers its information processing capabilities insufficient, or sees others as better informed than him.

Buckner (1965) explained that herding behavior may be caused by rumors. Schindler (2007) found that investors are frequently affected by rumors, either through social interactions or exposure to media reports, which are often unreliable. Individual investors tend to be more susceptible to such rumors, particularly during times of crisis when fear and uncertainty dominate the market, while professionals often benefit better from these rumors and make gains from them.

Guney, Kallinterakis and Komba (2017) also found that herding behavior exists strongly in African markets. Due to limited transparency that weakens the quality of their information landscape, investors rely on herding behavior to derive insights from the trading activities of their peers. Information asymmetry is also one of the most important factors leading strongly to herding behavior, as Kauffman and Li (2003) indicate that due to incomplete and inconsistent information in the stock market, decision-makers attempt to obtain higher value information by monitoring other people's procedures for obtaining information, to overcome inaccurate information for the decision-maker. In their study of 1,155 Chinese companies from 1999 to 2004, Bo, Li and Sun (2013) found that when companies operate in an environment of high uncertainty or significant information asymmetry, managers in these circumstances gather in crowds because this is considered safer for them.

Gavriilidis (2013) found that information was the most important element of successful investment; however, the process of collecting accurate information consumes a lot of time and money, so investors lacking sufficient information tend to replicate the decisions of those they perceive as more knowledgeable. Even those with dedicated media resources for data collection and analysis often opt to follow other investors when they believe their information is superior. This behavior, known as a "free ride", can ultimately result in a pattern of interconnected trading among investors.

The concept of information cascading has been widely explored in research on herding behavior, initially introduced by Banerjee (1992) and Bikhchandani, Hirshleifer and Welch (1992). They identified the information asymmetry among investors as a potential source of herding behavior and called it the "informational cascading". This information relay occurs when an investor decides to ignore her information collection and relies on information about other investors, as he works to mimic previous investors because he does not trust the information he possesses and this is thus reflected in his actions. Information cascading can negatively impact market efficiency, as it prevents all available information from being accurately reflected in stock prices.

Hirshleifer and Teoh (2003) assumed that the information cascading phenomenon caused information constraints, as not all investor information was transferred to the market. Bikhchandani, et al. (1992) explained that information cascading leads to increased herding behavior among investors. Information cascading is also initiated by a small number of individuals who have limited information so that the company that follows the crowd completely ignores its information or may not assign it the proper significance and blindly follows the decisions of others, which makes valuable information lost.

Many studies have tried to measure herding behavior through accurate scientific measures by which to assess the existence of herding behavior within financial markets and determine its proportion. Christie and Huang (1995) introduced a method known as Cross-Sectional Standard Deviation (CSSD) to measure dispersion and assess herding behavior in the market. This approach examines how individual stock returns deviate from the overall market portfolio return. If investors exhibit herding behavior, individual stock returns should closely align with market returns. The study analyzed market pressure during periods of significant market return fluctuations, assuming that investors set aside their personal beliefs and based their decisions on market consensus. Using dispersion analysis, the study evaluated daily and monthly NYSE and AMEX data from 1962 to 1988. The findings revealed that dispersion significantly increased during large price movements, aligning with rational asset pricing models and ultimately failing to confirm the presence of herding behavior.

Chang, Cheng and Khorana (2000) then introduced an innovative approach built upon the relationship between Cross Sectional Absolute Deviation (CSAD) and the market's unusual circumstances. The research investigated herding behavior across various global stock markets and found mixed results. While no evidence of herding was detected in developed markets, the findings indicated its presence in emerging markets like South Korea and Taiwan.

Hwang and Salmon (2004) also introduced an alternative approach in their study of the American and South Korean markets, utilizing the Cross-Sectional Standard Deviation of Betas. This model assumes that when investors exhibit behavioral biases – meaning their decisions are not entirely rational – their perception of the relationship between asset returns and risk becomes skewed. Consequently, if herding behavior is present in the market, the returns on all investments will align with the market portfolio, causing CAPM betas to diverge from their equilibrium values.

In the context of applied studies on market efficiency, a recent investigation by Litimi (2017) examined herding behavior within the French stock market. The study specifically aimed to assess this behavior's influence on idiosyncratic conditional volatility at the sectoral level. The research sample encompassed all firms listed on the French stock market, categorized by their respective sectors. The analytical period spanned from 2000 to 2016, encompassing four distinct economic crisis periods: the stock market downturn of 2002, the global financial crisis, the European sovereign debt crisis, and the Brexit event.

Abd-Alla (2020) investigated the presence of herding behavior in the Egyptian stock market during the COVID-19 crisis. The research utilized firm-level data and further examined herding at the portfolio level, categorized by size and value factors. To measure herding behavior, the study employed two distinct methodologies: the nonlinear model proposed by Chang et al. (2000) and the state-space model developed by Hwang and Salmon (2004). The findings presented a notable contrast between the two models. The nonlinear model by Chang et al. (2000) yielded results indicating evidence of herding during the COVID-19 crisis. Conversely, the state-space model by Hwang and Salmon (2004) revealed no evidence of herding behavior during the same period. At the portfolio level, herding was detected exclusively when applying the Chang et al. (2000) methodology, specifically in portfolios comprising stocks with low and high book-to-market (B/M) ratios and in the portfolio of large-cap stocks during the COVID-19 crisis.

In their investigation into investor behavior dynamics, a study conducted by Hudson, Yan and Zhang (2020) explored whether investor sentiment influences fund managers' herding behavior. The research utilized two composite indices as indicators of investor sentiment: the UK market-wide sentiment index and the UK institutional sentiment index. Herding behavior itself was quantified through the cross-sectional dispersion of factor sensitivity, specifically using beta. To examine the association between institutional herding and investor sentiment, the authors employed the Vector Autoregression (VAR) rule. The estimations provided evidence suggesting that herding behavior may not solely be driven by market fundamentals but also by investor sentiment. The findings distinctly indicated that both UK market-wide and institutional sentiment significantly impact the herding tendencies of UK open-ended fund managers. These observed effects demonstrated a unidirectional influence, thus supporting the proposition that investor sentiment serves as a key driver of herding.

Abd El-Razcek and Abd Elbaseet (2023) addressed the issue of herding behavior in the Egyptian stock market. The study aimed to test the existence of this behavior across various time periods, including the revolutionary era and the COVID-19 pandemic. Utilizing daily stock price data, the research employed an empirical analysis. Results generally indicated an absence of evidence for collective herding behavior in the Egyptian market. However, the models used revealed the presence of "adverse herding", characterized by a non-linear relationship. The study also noted that herding, when analyzed within sub-periods, represents a transient phenomenon linked to market classifications as bullish or bearish, and to changes in volatility levels. Conversely, in aggregated models, herding was observed in bullish markets with high volatility, while adverse herding emerged in bearish markets with low volatility.

Messaoud and Ben Amar (2025) investigated the relationship between herding behavior and investor sentiment in emerging stock markets (ESMs). The research aimed to determine the impact of sentiment on herding and the causal direction between them. Using daily data from several major emerging markets, the findings indicated that higher investor sentiment is generally associated with lower herding. However, during market downturns, elevated sentiment led to increased herding. The study also revealed a one-way causal relationship from investor sentiment to herding behavior. These results suggest that investor sentiment can contribute to irrational herding, potentially increasing market volatility and the likelihood of bubbles, underscoring the need for regulators to monitor sentiment to predict herding and stabilize markets.

Data And Methodology

Data

The study analyzed the impact of herding behavior on the efficiency of the Egyptian stock market using daily and monthly data from a 60-month period from 1/1/2014 to 31/12/2018[1]. It examined a sample of 50 stocks from the EGX100 index, which represents the top 100 active firms in the market. The data included stock closing prices, EGX100 index values, and monthly beta calculations for each stock.

The sample stocks were selected based on specific criteria: they must be traded in Egyptian pounds, exclude banks and financial institutions due to their unique characteristics, have continuous price data for 60 months, and be listed on the EGX100 index.

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[1] This period was selected for this study primarily to ensure the availability of complete and reliable data for the Egyptian stock market. This timeframe also represents a period of relative stability in market conditions, which facilitated a more accurate and robust analysis of herding behavior.

Methodology

Herding Behavior Measurement

The Hwang and Salmon (2004) model was applied to measure herding behavior in the Egyptian stock market. To calculate herding behavior values, the Hwang and Salmon (2004) model was based on the application of the State Space Model. Through the model, herding behavior can be estimated by logarithm Cross Sectional Standard Deviation of Betas Log [$Std_c(\beta^b_{imt})$], and to measure herding behavior, the following steps have been followed:

Calculating the daily stock return as well as the daily EGX 100 return by using the following equations:

Daily stock return

$$R_{it}=\frac{(P_t-P_{t-1})}{P_{t-1}} \tag{1}$$

Where R_{it} represents the return of stock i on day t, while P_t and P_{t-1} denote the closing prices of stock i on days t and t-1, respectively.

Daily EGX 100 return

$$R_{mt}=\frac{(P_{mt}-P_{mt-1})}{P_{mt-1}} \tag{2}$$

Where R_{mt} represents the return of EGX 100 index on day t, while P_{mt} and P_{mt-1} denote the closing prices of EGX 100 index on days t and t-1, respectively.

Calculating Excess Daily Return for each stock as well as the EGX 100 index:

The Excess Daily Return is calculated by deducting the risk-free rate from the daily return of each stock, as well as from the daily return of the EGX 100 market index.

Monthly Beta is calculated using the Ordinary Least Squares method (OLS) by the following regression formula:

$$r_{itd} = \alpha^b_{it} + \beta^b_{imt} r_{mtd} + \varepsilon_{itd} \tag{3}$$

Where r_{itd} and r_{mtd} represent the daily return of stock *i* and the EGX100 index during month *t*, respectively, while β^b_{imt} denotes the monthly beta for each stock.

The regression analysis was performed 60 times per stock to obtain monthly Beta per stock, thus the regression analysis was performed 3,000 times for all stocks. The Hwang and Salmon (2004) methodology is based on the Cross-Sectional Standard deviation of betas, as follows:

$$\frac{E^b_t(r_{it})}{E_t(r_{mt})} = \beta^b_{imt} = \beta_{imt} - h_{mt}\ (\beta_{imt} - 1) \tag{4}$$

Where E^b_t represents the expected return of stock i under behavioral bias, while $E_t(r_{mt})$ denotes the expected return of the market portfolio. h_{mt} represents the Herding behavior Coefficient, if (h_{mt} = 0) herding behavior is absent. Conversely, if (h_{mt} = 0), herding behavior is fully present, meaning individual stock returns move in sync with market portfolio returns.

Hwang and Salmon (2004) proposed the State Space Model to measure herding behavior using the change in stock sensitivity to change in market return through the following two equations:

$$\mathrm{Log}\ [\ Std_c(\beta^b_{imt})] = \mu_m + H_{mt} + v_{mt} \tag{5}$$

$$H_{mt} = \varphi_m\ H_{m,t-1} + \eta_{mt} \tag{6}$$

Where:

$\eta_{mt} \sim$ iid $(0, \sigma^2_{m,\eta})$

The model was estimated using the Kalman filter methodology within EViews software. The presence of herding behavior is inferred from the significant value of the variance of the error term η_{mt} ($\sigma^2_{m,\eta}$), and the significance of the persistence parameter (φ_m). Cross-Sectional Standard deviation of betas is calculated by the following formula:

$$Std_c(\beta)_t) = \sqrt{\frac{\Sigma^n_{i-1}(beta_{it} - \overline{beta_t}}{n-1}} \tag{7}$$

Statistical results of herding behavior

The study sample was divided into two different portfolios, as follows:

The portfolio shows herding behavior among investors, where herding behavior in this portfolio is statistically significant and consists of 18 stocks. A second portfolio, comprising 32 stocks, shows no statistically significant herding behavior.

Statistical Results of Herding Behavior

The stock sample is divided into two portfolios, each tested for herding behavior. Tables 1 and 2 present the statistical results for both portfolios.

Table 1. Statistical Results of the Space Model for the Portfolios in which Herding Behavior is Statistically Significant

	Coefficient	Std. Error	z-Statistic	Prob.	Variable	Estimate
C(1) µm	-0.001063	0.089924	-0.011821	0.9906	µm	-0.001063
C(2) vmt	-3.140787	0.348612	-9.009405	0.0000	σ_{mv}	0.20796333
C(3) ϕm	0.867566	0.194713	4.455622	0.0000	ϕ_m	0.86757
C(4) ηmt	-5.541811	1.936191	-2.862223	0.0042	$\sigma_{m\eta}$	0.06260529

Source: authors' construction.

Table 1 shows the state space model results for a portfolio consisting of 18 stocks of the sample. Coefficient c(1) represents (µm) in the state space model. The results indicated that it is not significant at the level of 5%. Coefficient c(2) represents the error term (υ_{mt}), and coefficients c(3) and c(4) refer to the persistence parameter (φ_m) and the standard deviation of the state-equation error (η_{mt}), respectively. The results indicated that they are statistically significant at the level of 5%, which confirms the presence of herding behavior.

Table 2. Statistical Results of the Space Model for the Portfolios in which Herding Behavior is not Statistically Significant

	Coefficient	Std. Error	z-Statistic	Prob.	Variable	Estimate
C(1) μm	-0.147764	0.019455	-7.595299	0.0000	μm	-0.147764
C(2) vmt	-21.7119	1.48E+10	-1.47E-09	1.0000	σ_{mv}	1.9289E-05
C(3) ϕm	0.023413	8.687411	0.002695	0.9978	ϕ_m	0.023413
C(4) ηmt	-4.21498	373.3079	-0.011291	0.9910	$\sigma_{m\eta}$	0.12154266

Source: authors' construction.

Table 2 presents the state-space model results for a portfolio of 32 stocks. The findings indicate that coefficients c(3) and c(4), representing the persistence parameter (φ_m) and the standard deviation of the state-equation error (η_{mt}), are not statistically significant at the level of 5%, confirming the absence of herding behavior.

Efficiency Testing

Market efficiency was analyzed in two portfolios: one exhibiting statistically significant herding behavior and another where herding was not significant. Efficiency was assessed based on the weak form of efficient markets, as defined by Fama (1970), which states that stock prices should be normally distributed, independent, and unpredictable. The evaluation process involved the following steps:

- Normality Test: The Shapiro-Wilk and Kolmogorov-Smirnov tests were used to check if stock prices followed a normal distribution;
- Dickey-Fuller Unit Root Test: Applied to determine whether the time series data was stationary or non-stationary;
- Runs Test: Used to assess whether stock price movements followed a random pattern.

Descriptive Statistics

Table 3 presents the descriptive statistics for both portfolios: one where herding behavior is statistically significant and another where it is not. The results indicate that the time series for both portfolios exhibit right-skewed distributions. The skewness coefficient is 0.546 for the portfolio with herding behavior and 0.463 for the portfolio without it.

Table 3. Descriptive Statistics

The portfolio shows herding behavior		The portfolio does not show herding behavior	
Mean	19.6767	Mean	21.5867
Median	16.6518	Median	20.6888
Variance	74.068	Variance	122.926
Std. Deviation	8.60626	Std. Deviation	11.08721
Minimum	6.94	Minimum	6.43
Maximum	36.71	Maximum	46.69
Range	29.77	Range	40.26
Skewness	0.546	Skewness	0.463
Kurtosis	-1.042	Kurtosis	-0.871

Source: authors' construction.

Testing the Normal Distribution of Time Series

The Shapiro-Wilk and Kolmogorov-Smirnov tests were performed to assess whether the time series follows a normal distribution. The results in table 4 show that Sig. Value is at less than 5%. Therefore, stock prices do not normally distribute and are independent for both the portfolio that shows herding behavior and the portfolio that does not show herding behavior. Therefore, the two portfolios do not achieve a weak level of efficiency.

Table 4. Time-Series Natural Distribution Test

	The portfolio shows herding behavior			The portfolio does not show herding behavior		
	Statistic	df	Sig.	Statistic	df	Sig.
Kolmogorov-Smirnov	0.156	1220	0.000	0.099	1220	0.000
Shapiro-Wilk	0.905	1220	0.000	0.905	1220	0.000

Source: authors' construction.

Testing Random Behavior of the Time Series

This study analyzes the randomness of the time series using various statistical methods, including:

The Runs Test

The Runs test is used to examine the randomness of data. Table 5 shows the results of the Runs test. The results show that the p-value is less than 5%, as the p-value is equal to zero for both the portfolio showing herding behavior and the portfolio does not showing herding behavior. Thus, the time series of each portfolio is non-random, which indicates that the two portfolios do not achieve a weak level of efficiency.

Table 5. The Runs Test Results

	The portfolio shows herding behavior	The portfolio does not show herding behavior
Test value	16.65	20.69
Number of Runs	14	12
Z-statistic	-34.198	-34.313
p-value	0.000	0.000

Source: authors' construction.

Unit Root Test for Dickey-Fuller

The Unit Root Test for Dickey-Fuller, or the so-called Augmented Dickey-Fuller test (ADF test), is used to study the stationary and stability of the time series. If the time series is static and does not move randomly, this means that the market is inefficient according to the weak level. Table 6 shows the results of the Unit Root test, which indicates that the ADF test statistic is smaller than the critical values at 1%, 5%, and 10%. The value of the p-value is also less than 5%, as it is equal to zero for both portfolios showing herding behavior and those that do not show herding behavior. Therefore, these results show that there is no unit root in the return series of the two portfolios, which indicates incompetence at the weak level of each portfolio.

Table 6. Unit Root Test for Dickey-Fuller

		The portfolio shows herding behavior	The portfolio does not show herding behavior
critical value	1%	-3.969876	-3.969845
	5%	-3.415595	-3.41558
	10%	-3.130037	-3.130028
ADF test statistic		-19.0147	-26.59111
p-value		0.0000	0.0000

Source: authors' construction.

Conclusion

This paper examined the impact of herding behavior on market efficiency in the Egyptian stock market. The main sample of the research was divided into two sub-samples: the first sample is a portfolio of stocks showing herding behavior and the second sample is a portfolio of stocks that does not show herding behavior. The efficiency was tested using the Runs test and the Dickey-Fuller Unit Root Tests, in addition to applying the Hwang and Salmon (2004) methodology to test herding behavior. Through statistical results, the time-series prices of both the portfolio showing herding behavior and the portfolio does not show herding behavior, are not going randomly, as the results of the Runs test and the Dickey-Fuller Unit Root Tests are consistent and supportive of each other. Therefore, the two portfolios do not achieve a weak level of efficiency. Thus, we can conclude that herding behavior among investors in the Egyptian stock market does not affect market efficiency. Therefore, other factors, rather than herding behavior, may influence the efficiency of the Egyptian stock market.

There may be a relationship between herding behavior and inefficient financial markets, but due to several limitations in this research, this relationship was not as clear as the results showed. One of the limitations is the small size of the sample, it is advisable to use a larger sample size to achieve different results more accurately. Additionally, the period of study was only 5 years. For future studies, it is advisable to consider a study period longer than 5 years, as well as utilizing different measures of herding behavior, which may yield varied findings.

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