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RESEARCH PAPER

Dynamic Conditional Correlation Analysis of Investor Herding: Evidence from the Indonesian and Malaysian Capital Markets

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Abstract
This paper applies the Dynamic Conditional Correlation (DCC) multivariate GARCH model by including a volatility index to examine herding behavior. We analyzed whether stock return dispersion to the market return has a time-varying conditional correlation in the Indonesian and Malaysian capital markets. We used daily returns data of blue-chip stock and LQ45 & KLCI index for the period January 2015 – December 2022 to capture herding effects among the investors of both capital markets. The main findings demonstrate herding behavior in bullish markets before the pandemic, but only for the LQ45 and not for the KLCI. Herding will result in lower market returns. We further establish that the volatility index exhibits significant positive changes in a bearish condition amidst the epidemic in both indexes. These findings suggest that while institutional and long-term investors dominate the market for blue-chip companies, they nonetheless make investment decisions based on the majority under specific circumstances. The partial presence of herding behavior and anxiety indices in the market provides support for the behavioral finance theory, which suggests that individuals may exhibit irrational behavior.

Keywords: Dispersion, DCC GARCH, Multivariate, Volatility.
JEL Classification: C22, C58, G41.

1. Introduction
Herding is a part of human instinct widely discussed in behavioral research. Herding is a phenomenon characterized by individuals observing others' behavior and subsequently conforming to the majority (Botsvadze, 2013). As a manifestation of collective behavior, herding is influenced by the psychological

comfort derived from imitating others (Haghani and Sarvi, 2019). Concerns about appearing "different" from others in the market indicate a facet of social conformity (Baddeley, 2015). This behavior has been identified and labeled as convergence behavior by Hirshleifer and Teoh (2003). In financial markets, herding refers to investors who conform to prevailing market patterns, often disregarding their information analysis (Bikhchandani and Sharma, 2001). It can be caused by information asymmetries, where not all investors can access available information. Herding manifests when the market experiences stress or crises. Excessive market volatility and asset price deviations from their fundamental values are adverse effects of herding (Alber and Ezzat, 2021).

Although numerous studies investigate the impact of herding, relatively few analyze the specific attributes of the resulting financial data volatility. The phenomenon of volatility clustering and time-varying characteristics in financial data is known as herding (Chen et al., 2021). The clustering of high and low volatility in asset prices and returns is referred to as volatility clustering in time series data. The assumption of constant error variance is frequently violated, and heteroscedasticity may manifest (Ogata, 2012; Stojanovski, 2015; Rice et al., 2020). Heteroscedasticity can introduce bias or spuriousness into parameter estimates in statistical models (e.g., regression coefficients), which may lead to misleading conclusions (Gujarati and Porter, 2009; Lauridsena and Kosfeld, 2011; Farbmacher and Kögel, 2017). The model must be efficient (Shahraki et al., 2021). This issue is a frequent practice that is often overlooked.

Hence, the Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity or DCC-GARCH (Engle, 2002) is an alternative solution to address the presence of heteroscedasticity or leptokurtic error data distribution. The DCC-GARCH model can estimate the time-varying relationship between variables. This model posits that the residual's square and the previous residuals' variance affect the current residual variance. The DCC-GARCH model arguably offers several advantages, but its application in herding analysis remains constrained. Hence, this study employs the DCC-GARCH with Normal and Student’s-t distribution to identify herding behavior within a specific temporal interval.

Time-varying characteristics refer to bullish/bearish market periods as part of investors' demand/supply dynamics. Bullish conditions represent investors' optimism to buy shares that increase prices, while bearish conditions indicate investors' pessimism, leading to price decline (Rout et al., 2017). However, the COVID-19 pandemic has greatly impacted countries, including global financial markets and developed countries (Contessi and Pace, 2021). Hence, it is imperative to investigate herding in Indonesia and Malaysia, considering their status as growing economies within the ASEAN Economic Community. This research exerts significant importance within the economic and financial landscape. Both capital markets exhibit a high degree of openness towards foreign investors and have a notable expansion rate. This argument is supported by adopting regulatory measures to improve transparency, liquidity, and accessibility in financial markets. The Financial Services Authority reported that the Indonesia Stock Exchange/IDX experiences a significant daily value of share trading, surpassing 14.000 IDR billion. This trading activity is mostly driven by domestic investors, with retail investors being the majority, accounting for 72% of the total (OJK, 2022). Meanwhile, according to the Malaysian Stock Exchange Authority (2023), a notable presence of local investors accounts for over 86% of the total investors. This majority comprises retail investors, government institutions, and nominees. Retail investors exhibit traits such as uninformed trading (Baig et al., 2022), where they make investment decisions primarily influenced by market movements or the prevailing consensus.

Prior herding studies document inconsistent results from varying analysis methods in both markets. Rizal and Damayanti (2019) observe herding behavior in the bearish market of the Jakarta Islamic Index using GARCH analysis. Further, Putra et al. (2017) utilize the CSAD-OLS analysis and reveal that Indonesian investors exhibit stronger herding behavior than Singaporean investors. In contrast, Fransiska et al. (2018) cannot document herding behavior on the IDX using stock return data in LQ45. Rahman and Ermawati (2020) analyze herding behavior in the ASEAN (Indonesia, Singapore, Malaysia, Philippines, and Thailand) and the U.S. stock market. They utilize the Newey-West estimator and demonstrate that only market crashes display herding tendencies. Meanwhile, Ah Mand and Sifat (2021) report inconclusive findings of the CSSD and CSAD models when employing OLS. On the other hand, a dynamic methodology with a two-state Markov Switching model demonstrates that herding is strongly regime-dependent and non-linear.

Previously, the literature on herding tests utilizing the DCC GARCH model was comparatively scarce, particularly concerning pandemic phenomena with complex global impacts. This study compares the effectiveness of the DCC-GARCH analysis model and the ordinary least squares (OLS) method in accurately capturing the optimal model during dynamic periods. We evaluate herding behavior, namely the volatility index (VIX), using a dynamic correlation analysis and a time-varying analysis. The VIX, also known as the Chicago Board Options Exchange Volatility Index (Brenner and Galai, 1989), measures global market uncertainty. Braiek and Jeribi (2022) indicate that higher levels of uncertainty, as measured by increased VIX ratios, lead to a stronger correlation between assets in different sectors. Essa and Giouvris (2023) examine the influence of VIX and discover that herding increases in response to heightened levels of investor uncertainty and fear. To the best of our knowledge, there is a scarcity of literature that examines the evolution of herding within both market settings. The DCC-GARCH approach exhibits the distinctive feature of uncovering the conditional correlation between beta and herding. This study contributes to the behavioral finance literature by demonstrating the comparative superiority of dynamic models in explaining the herding phenomenon.

This paper is organized as follows: Section 2 of this study presents a comprehensive literature review and formulates hypotheses. Section 3 discusses the data collection and methodology employed in the study. Section 4 entails the presentation and interpretation of empirical data, while Section 5 concludes.

2. Literature Review

2.1 The Herding Concept

The efficient market hypothesis posits that the price of a financial asset reflects all pertinent information (Fama, 1970). There exists a strong correlation between the level of market efficiency and the availability of this particular information, consisting of historical and public information (weak-form efficiency), historical, public, and insider information (semi-strong-form efficiency), or all private and public information (strong-form efficiency). However, not all investors possess the same level of information as presumed by the efficient market hypothesis. Investors in efficient markets cannot generate abnormal returns by exerting control over the market (Malkiel, 2003). Conversely, psychological factors may affect investors' irrational behavior in making decisions. Although price formation is not the primary concern of efficient market theory, behavioral finance has emerged, which encompasses the study of herding behavior.

Herding refers to the phenomenon in which investors imitate the activities of the majority or other market participants without critically evaluating available information (Kumar et al., 2021). Market information asymmetry motivates several individuals to conform to the majority, which is presumed to possess more information (Scharfstein and Stein, 1990). Herding is a behavioral tendency to imitate others' actions rather than one's own information beliefs, regardless of how those actions are perceived (Christie and Huang, 1995). If investors follow the majority, the distribution of returns will be nonexistent (homogeneous). Thus, investors feel secure, particularly when they are hesitant to act independently. Also contributing to concerns is the fear of missing out (FOMO) associated with missing trends or opportunities [see (Gupta and Shrivastava, 2022) and (Bo, 2023)].

Herding illustrates the correlation that exists between shareholder interactions. Chang et al. (2000) empirically demonstrate herding behavior in the South Korean and Taiwan markets, and to some extent, the Japanese market. On the one hand, herding behavior increases market volatility because numerous investors sell or buy large amounts of assets simultaneously. This phenomenon affects financial asset valuation, leading to mispriced assets. On the other hand, volatility arguably elicits investors' emotional responses, including anxiety and uncertainty. Greater market volatility is associated with higher systemic risk. Hence, investors commonly seek market signals or rely on collective behavior to navigate through uncertain periods. This phenomenon might elicit herding behavior among investors, wherein they collectively engage in actions to mitigate risk or capitalize on opportunities.

Arjoon et al. (2020) observe that the time-varying herding in most size-based portfolios typically exhibits similar behavior to the overall market. Intentional herding is observed in the overall market and is particularly prevalent during bullish markets. However, Bohl et al. (2017) re-examine the herding measure proposed by Chang et al. (2000) for the S&P 500 and the EuroStoxx50. Their findings confirm that the CSAD measure has misleading consequences: the true coefficient is positive under the null hypothesis of no herding. A supplementary analysis investigates the impact of global market volatility on herding. Andrikopoulos et al. (2017) discovered that cross-border transactions on the Euronext exhibit varied herding dynamics. They observe significant intraday herding before and after the 2007-2009 financial crisis, with the highest occurrence during the market crisis. Kumar et al. (2021) document the occurrence of herding behavior in commodities markets across the Asia-Pacific region, encompassing China, India, Japan, Malaysia, Singapore, Taiwan, and Thailand, particularly during periods of heightened market volatility. According to Asadi et al. (2022), herding on the Tehran Stock Exchange is statistically significant at the 1% level but insignificant when considering the overall market. Herding is particularly evident amid major fluctuations in other commodities such as gold and currency prices.

Investors may experience emotional responses, including anxiety and uncertainty, in response to volatility. Systemic risk may increase when excessive volatility is prevalent across financial markets. Investors typically seek out other investors' signals and actions to help them mitigate uncertainty during periods of high volatility. Herding behavior may ensue, whereby investors imitate the actions of their peers to evade risks or seize opportunities. Herding behavior may occasionally catalyze heightened volatility. When numerous investors collectively engage in comparable activities, such as selling substantial assets, the market may experience heightened volatility due to intense selling pressure.

Beta can be used to measure the volatility of a financial asset or market. Non-volatile stocks or markets are characterized by a small beta (<1) and vice versa. In the CAPM context (Sharpe, 1964), beta is assumed to be constant over time and is estimated via ordinary least squares (OLS). However, there is widespread evidence in the market that beta risk fluctuates over time [Nieto et al. (2014); Brooks et al. (1998); Fabozzi and Francis (1979)]. Based on this evidence, defining beta as a series of conditional time changes is appropriate. Recent literature has applied several econometric methods to estimate time-varying betas across countries (McKenzie et al., 2001). Extensive studies have used the GARCH model for beta volatility (Chen et al., 2021). Due to multiple return dispersion-measuring variables, the one-dimensional GARCH model is not an optimal analysis method. This study's beta estimation method for multiple variables is dynamic conditional correlation (DCC), implemented within the multidimensional GARCH model.

Engle (2002) developed dynamic conditional correlation (DCC) by modelling variance and conditional correlation on time variables, which enables the mitigation of asymmetric volatility dynamics. Park and Kim (2017) and Tsionas et al. (2022) have employed dynamic measurement models to investigate herding behavior within the U.S. capital market. Ferreruela et al. (2022) investigate herding in the context of ten Asia-Pacific markets from February 1995 to March 2022. Samitas et al. (2022) empirically investigate the impact of the pandemic on stock markets using the DCC model to test correlations (bonds, stock indices, and credit default swaps) between countries (emerging and developed markets).

2.2 Herding Measurement

In the herding context, the use of return dispersion pertains to quantifying the variability of the returns of different assets comprising a given portfolio. Investor behavior can be statistically measured by calculating the similarity or divergence of the dispersion. Herding behavior is indicated by the low level of return dispersion, which occurs when investors make relatively similar investment decisions, resulting in nearly identical increases or decreases in investment returns. Conversely, higher dispersion rates of returns signify substantial variation in investment returns or investors making various decisions to avoid conforming to the majority. Rational investors (Fama, 1970) use CAPM (Sharpe, 1964) to guide decision-making concerning the balance of returns and risks. Nevertheless, Hirshleifer and Teoh (2003) caution against the possibility of investor bias arising from investors' imperfect cognitive abilities and social dynamics such as herding. One can assess a market's efficiency or irrationality (herding) by examining its return dispersion.

Christie and Huang (1995) employ the dispersion of individual stock returns during significant cross-sectional price changes (CSSD) to quantify herding. Hwang and Salmon (2004) developed this model by using the standardized standard deviation of factor loadings to measure the degree of herding. They observe herding during periods of market calmness as opposed to periods of depressed markets in the U.S. and South Korea. Herding occurs when investors adhere more closely to the overall market performance. Investors purchase assets with a beta value below one on the assumption that they are relatively inexpensive, while selling assets with a beta value above one because they are already costly in comparison to the market. In their study, Chang et al. (2000) employ cross-sectional absolute deviation (CSAD) to quantify the non-linear nature of return dispersion. Chiang and Zheng (2010) expand CSAD in various markets (bullish and bearish).

Previous research documenting herding behavior enables us to hypothesize herding behavior in the Indonesian and Malaysian capital markets before and during the pandemic. The financial crisis caused by the COVID-19 pandemic will likely affect herding behavior. This research considers the periods to differentiate the herding phenomenon in normal market conditions in the long term and crisis conditions in the short term. Therefore, this study uses a recent daily data set spanning eight years to test this hypothesis. We also hypothesize that herding occurs in different market conditions (bullish and bearish) over that period. We also predict that the volatility index will influence investor herding, as indicated by the high Volatility Index as a reflection of investors' anxious reactions in the wake of the pandemic.

3. Methods and Materials

3.1 Data

This study generated the stock data from www.idx.co.id and www.bursamalaysia.com, while the daily closing price data of stocks, stock indices, and volatility indices were obtained from www.yahoofinance.com and www.investing.com. Our population is firms listed in the LQ45 (Indonesia Stock Exchange) and FTSE KLCI (Bursa Malaysia) indices, representing a group of stocks with high capitalization, large transaction values, and excellent financial performance. We utilized the purposive *sampling* techniques based on the criteria of stocks continuously listed from 2015 to 2022.

3.2 Herding Models

Our herding measurement uses the dispersion of stock returns on portfolio/market returns. Stock returns (R_{it}) are calculated by dividing the price of stock *i* in period *t* by its price at the previous period (*t-1*), as illustrated by the following formula:

$$R_{it} = \frac{P_{it} - P_{i\,(t-1)}}{P_{i\,(t-1)}} \quad (1)$$

where P_{it} and $P_{i\,(t-1)}$ are the closing price of individual stocks of LQ45 or FTSE KLCI firm at time *t* and $t-1$. The calculation of market returns (R_{mt}) in period *t* is:

$$R_{mt} = \frac{P_{mt} - P_{m\,(t-1)}}{P_{m\,(t-1)}} \quad (2)$$

where, P_{mt} and $P_{m\,(t-1)}$ are the closing index of LQ45 or FTSE KLCI on period *t* and $t-1$.

Return dispersion of the cross-sectional standard deviation (CSSD) can be utilized to detect herding (e.g., Christie and Huang 1995). The relationship between the CSSD of dispersion of individual stock returns and market return is linear. The estimation indicates that rational asset pricing models and herding will produce opposite consequences. Herding is (not) observed when the correlation value of the dispersion is low (high). Despite being an intuitive measure, this model is significantly impacted by outliers in the linear correlation of the data. Subsequently, Chang et al. (2000) propose a more suitable metric, the cross-sectional absolute deviation (CSAD) of stock requationlative to the market portfolio returns. The CSAD is calculated as follows:

$$CSAD_t = \Sigma_{i=1}^{N} \frac{|R_{it} - R_{mt}|}{N} \quad (3)$$

where N is the number of shares in the portfolio.

The relationship $CSAD_t$ and R_{mt} is a form of non-linear regression expressed below.

$$CSAD_t = \alpha + \gamma_1 R_{mt} + \gamma_2 R_{mt}^2 + \varepsilon_t \quad (4)$$

Herding is present if the negative coefficient γ_2 is significant, and conversely, herding is not present when the positive coefficient γ_2 is significant. The quadratic relation suggests that $\mathrm{CSAD_t}$ reaches its maximum value when $\mathrm{R_{mt}} = -(\gamma_1/2\gamma_2)$. That is, as $\mathrm{R_{mt}}$ increases, over the range where realized average daily returns are less (greater) than $\mathrm{R_{mt}}$, $\mathrm{CSAD_t}$ is trending bull/bear (Chang et al., 2000).

Chiang and Zheng (2010) add a formula with the asymmetric conditions of a bull market ($\mathrm{R_{mt}}$>0) and a bear market ($\mathrm{R_{mt}}$<0). Another important problem is whether herding has a relation with the volatility index. If so, the implication is that herding exists more when the market is overwhelmed by investors' anxiety. We use the CBOE Volatility Index (VIX) variable within equation 5 as follows:

$$\mathrm{CSAD_t} = \alpha + \gamma_1 \mathrm{R_{mt}} + \gamma_2 |\mathrm{R_{mt}}| + \gamma_3 \mathrm{R^2_{mt}} + \beta Vix + \sigma_t^2 + \varepsilon_t \quad (5)$$

$$\mathrm{CSAD_t^{Bull}} = \alpha + \gamma_1 \mathrm{R_{mt}} + \gamma_2 \left|\mathrm{R_{mt}^{Bull}}\right| + \gamma_3 (\mathrm{R_{mt}^{Bull}})^2 + \beta \mathrm{V}ix + \sigma_t^2 + \varepsilon_t \quad \text{if } \mathrm{R_{mt}} > \text{median} \quad (6)$$

$$\mathrm{CSAD_t^{Bear}} = \alpha + \gamma_1 \mathrm{R_{mt}} + \gamma_2 \left|\mathrm{R_{mt}^{Bear}}\right| + \gamma_3 (\mathrm{R_{mt}^{Bear}})^2 + \beta \mathrm{V}ix + \sigma_t^2 + \varepsilon_t \quad \text{if } \mathrm{R_{mt}} < \text{median} \quad (7)$$

where $\mathrm{R_{mt}^{Bear}}$ is the bearish market return at time *t*, and $\mathrm{R_{mt}^{Bear}}^2$ denotes the square value of the market return as a non-linear relationship during bearish market periods. $\mathrm{R_{mt}^{Bull}}$ represents the bullish market return at time *t*, and $\mathrm{R_{mt}^{Bull}}^2$ denotes the square value of the market return as a non-linear relation of periods of a bull market. $\mathrm{CSAD_t^{Bear}}$ is the dispersion of stock returns at time *t* during bearish market conditions, and $\mathrm{CSAD_t^{Bear}}$ refers to the dispersion of stock returns at time *t* during bearish market conditions. Vix is the value of the volatility index on day *t*. A significant and negative Vix would imply that a rise in market stress and fear regarding economic conditions would make investors follow the market consensus, contributing to a hike in herding behavior and vice versa.

Before measuring herding, it is necessary to assess the stationarity of the data using the unit root test. The test is capable of determining whether or not a time series contains a unit root. A unit root occurs when the root of a time series is approximately equal to one (1), signifying that the series is non-stationary with respect to its mean. The model for unit root testing is as follows.

$$\Delta Y_t = \alpha_1 + \gamma_1 + \beta_1 Y_{t-1} + \sum_{i=1} \delta_t \Delta Y_{t-1} + \varepsilon_t \quad (8)$$

The following hypothesis is compiled based on the Augmented Dickey-Fuller (ADF) value results.

$\mathrm{H_0}$: $\delta = 0$: Time series data has a unit root, indicating non-stationarity.

$\mathrm{H_1}$: $\delta \neq 0$: Time series data does have a unit root, indicating stationarity.

The interpretation of the ADF test results is as follows: $\mathrm{H_0}$ is not rejected when the ADF test statistic exceeds the critical value, but is accepted when the statistic is less than the critical value (<0.05). The ARCH (Autoregressive Conditional Heteroskedasticity) test is continued to ascertain the subsequent mode of analysis once the data has become stationary. In time series data, the ARCH test is utilized to identify and model conditional heteroskedasticity. The following hypothesis was constructed using the ARCH-LM (Lagrange Multiplier) test results.

H_0 : The squared residuals exhibit no residual autocorrelation.

H_1 : The squared residuals exhibit residual autocorrelation.

The results of the ARCH-LM test can be interpreted as follows: H_0 is rejected (supported) if the test statistic is greater (lower) than the critical value.

3.3 Dynamic Conditional Correlation GARCH

Engle (1982) introduces ARCH to overcome non-constant error variance in financial time series data where the error variance (σ_t^2) is strongly influenced by errors in the previous period (e_{t-1}^2). Bollerslev (1986) extends ARCH into Generalized Autoregressive Conditional Heteroskedasticity (GARCH), where error variance (σ_t^2) depends not only on errors in the previous period (e_{t-1}^2) but also error variance in the previous period (σ_{t-1}^2). GARCH is developed by including quadratic error elements and period errors variance into the ARCH model to avoid excessive lag. The GARCH model specification is:

$$\begin{gathered}\sigma_t^2 = a_o + a_1 e_{t-1}^2 + \cdots + a_1 e_{t-p}^2 + \lambda_1 \sigma_{t-1}^2 + \cdots + \lambda_p \sigma_{t-q}^2 \\ \text{with } e_t = \sigma_t\, x_t, x_t \sim i.i.d\; N\;(\mu, \sigma^2), a_o > 0 \text{ and } a_t \geq 0 \text{ for } i = 0\end{gathered} \tag{9}$$

Furthermore, Engle (2002) modifies GARCH by modifying the Dynamic Conditional Correlation (DCC) GARCH framework that combines each asset's volatility measurement components and a dynamic correlation model to measure the relationships between those assets. DCC-GARCH offers the advantage of handling dynamic rather than static correlation and can accommodate non-normally distributed data (Robiyanto, 2018).

The model suggests that the covariance matrix (H_t) can be composed into a conditional standard deviation (D_t) and a correlation matrix (R_t). Both models (D_t and R_t) are designed to be time-varying. The following is the DCC GARCH equation:

$$\begin{aligned} r_t &= \mu_t + a_t \\ a_t &= H_t^{1/2} a_t\, z_t \\ H_t &= D_t R_t D_t \end{aligned} \tag{10}$$

where

r_t : $n\ x$ 1 vector of log returns of *n* assets at time *t.*

a_t : $n\ x$ 1 vector of mean-corrected returns of *n* assets at time *t*, i.e. $\mathrm{E}[a_t] = 0$. $\mathrm{Cov}[a_t] = H_t$.

μ_t : $n\ x$ 1 vector of the expected value of the conditional r_t.

H_t : $n\ x\ n$ matrix of conditional variances at a_t time *t.*

$H_t^{1/2}$: $n\ x\ n$ matrix at time *t*. such that H_t is the conditional variance matrix of a_t. $H_t^{1/2}$ may be obtained by a Cholesky factorization of H_t.

D_t : $n\ x\ n$ as the diagonal matrix of conditional standardized deviation of a_t in time *t*.

R_t :$n\ x\ n$ as a conditional matrix of a_t in period *t*.

z_t : $n\ x$ 1 vector of iid errors such that $\mathrm{E}[z_t] = 0$ and $\mathrm{E}[z_t z_t^T] = 1$.

The elements in the diagonal matrix (D_t) represent the standard deviations of the univariate GARCH model.

$$D_t = \begin{bmatrix} \sqrt{h_{1t}} & 0 & \cdots & 0 \\ 0 & \sqrt{h_{2t}} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sqrt{h_{nt}} \end{bmatrix} \tag{11}$$

where $h_{i,t} = a_{i0} + \sum_{q=1}^{Q_1} \alpha_{iq}\ \alpha_{i,t-q}^2 + \sum_{p=1}^{P_1} \beta_{iq}\ h_{i,t-q}^2$, R_t is a correlation matrix. R_t is the conditional correlation matrix of the standardized residuals ε_t, i.e.: $\varepsilon_t = D_t^{-1} a_t \sim N(0, R_t)$.

Since R_t is a correlation matrix, it is symmetric.

$$R_t = \begin{bmatrix} 1 & \rho_{12,t} & \rho_{13,t} & \cdots & \rho_{1n,t} \\ \rho_{12,t} & 1 & \rho_{23,t} & \cdots & \vdots \\ \rho_{13,t} & \rho_{23,t} & 1 & \ddots & \vdots \\ \vdots & \vdots & \ddots & \ddots & \rho_{n-1,n,t} \\ \rho_{1n,t} & \rho_{2n,t} & \cdots & 0 & 1 \end{bmatrix} \tag{12}$$

The elements of $H_t = D_t R_t D_t$ are:

$$[H_t]_{ij} = \sqrt{h_{it} h_{jt\rho_{ij}}}$$

where $\rho_{ii} = 1$. To ensure both of these requirements in the DCC-GARCH model, R_t is decomposed into (Jabalameli et al., 2020):

$R_t = Q_t^{*-1} Q_t Q_t^{*-1}$and $Q_t = (1 - \alpha - \beta)\overline{Q} + \alpha \varepsilon_{t-1} \varepsilon'_{t-1} + \beta Q_{t-1}$

where Q_t^* is a diagonal matrix consisting of the square roots of the diagonal elements of the matrix Q_t, thus $Q_t^* = Diag(Q_t)^{1/2}$.

4. Results

4.1 Descriptive Statistics

The descriptive statistics for the entire dataset are presented in Table 1. These statistics include observation numbers (N), the average returns dispersion (CSAD), average stock returns (R_i), and average market returns (R_{mt}) of FTSE KLCI, which are 1951 days, -0.01 percent, -0.53 percent, and 0.02 percent, respectively, with standard deviations of 0.72 percent, 0.85 percent, and 0.73 percent.

Meanwhile, observation numbers (N), the average returns dispersion ($CSAD_t$), average stock returns (R_i), and average market returns (R_{mt}) of LQ45 are 1968 days, 1.01 percent, 0.03 percent, and -0.02 percent, respectively, with standard deviations of 1.15 percent, 1.17 percent, and 1.32 percent. The overall average values data of the volatility index (Vix) is 18.68 with a standard deviation of 7.91. Under all data conditions, the excess kurtosis value (>3) is leptokurtic (abnormal curve). A leptokurtic distribution can be visualized as a thin 'bell' with a high peak (Kalner, 2018), as the GARCH models require.

Table 1. Descriptive Statistics

Index	Var	N	Mean	Median	Max.	Min.	Std Dev.	Kurtosis
KLCI	$CSAD_t$	1951	0.0053	0.0027	0.0655	0.0001	0.0072	16.73
	R_i		0.0002	0.0002	0.0627	-0.0871	0.0089	14.64
	R_{mt}		-0.0001	-0.0001	0.0685	-0.0526	0.0073	11.27
LQ45	$CSAD_t$	1968	0.0101	0.0065	0.1489	0.0001	0.0115	24.64
	R_i		0.0003	0.0008	0.0947	-0.0836	0.0117	10.08
	R_{mt}		-0.0002	0.0001	0.1492	-0.0826	0.0132	14.90
CBOE	Vix		18.68	16.54	82.69	9.14	7.91	14.21

a. Test distribution is not Normal.
b. Calculated from data

Source: Research finding.

Figure 1 shows the volatility graph of the daily returns of both indices. The residuals of both indices fluctuate and deviate from their means. In that case, analyzing the conditional variance of returns is necessary. Thus, heteroscedasticity needs to be tested for the returns of both indexes (ARCH test).

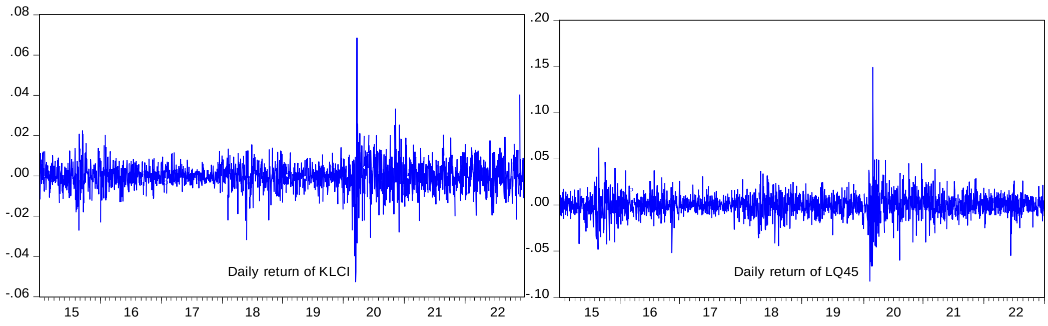

Figure 1. Daily Returns of the Indices for 8 Years.
Source: Research finding.

4.2 Stationarity Test

The null hypothesis of the stationarity test based on the Augmented Dickey-Fuller (ADF) value results that the data have a unit root, indicating non-stationarity (Eq. 7). Table 2 shows that all data for measuring research variables have significant *p*-values (<0.05). Therefore, all data in this study are stationary (H_0 is rejected) and do not have a unit root at the level.

Table 2. Unit Root Test

		ADF Test	Prob.
KLCI	$CSAD_t$	-6.9110	0.0000
	R_i	-49.7903	0.0001
	R_{mt}	-10.8249	0.0000
LQ45	$CSAD_t$	-7.8214	0.0000
	R_i	-8.9377	0.0000
	R_{mt}	-42.5447	0.0000
CBOE	Vix	-4.8023	0.0001

Source: Research finding.

4.3 ARCH-LM Test

The ARCH-LM test results (Table 3) suggest that the p-values of these statistics imply that the correlation between residuals is insignificant in all lags (<0.05) or H_0 is rejected. The ARCH-LM test implies the presence of a conditional heteroscedasticity problem in all time series. Therefore, in order to model the conditional variances of the aforementioned models, the following DCC GARCH (1,1) model will be used.

Table 3 Heteroscedasticity Test

KLCI	F-statistic	7.7029	Prob. F (1.1756)	0.0000
	Obs.*R-squared	1.4330	Prob. Chi-Square (1)	0.0000
LQ45	F-statistic	14.8981	Prob. F (1.1756)	0.0001
	Obs.*R-squared	14.8023	Prob. Chi-Square(1)	0.0001

Source: Research finding.

Note: The heteroscedasticity test is conducted using the ARCH-LM method. A test statistic lower (higher) than the critical value indicates the presence (absence) of heteroscedasticity in the data.

4.4 DCC GARCH Model

Table 4 presents the estimation results for DCC-GARCH (1,1) with Student's t distributions have a smaller AIC than the normal distribution, are free from heteroscedasticity problems (ARCH>0.05), and have a significant variance equation (<0.05). The analysis reveals that the value of γ_3 is insignificantly negative (>0.05), indicating that the KLCI investors did not exhibit herding behavior in the overall data (2015-2022 periods). Likewise, OLS analysis produces insignificantly negative values of γ_3 (>0.05), but the data exhibits heteroscedasticity problems (ARCH<0.05). The findings indicate that investors tend to exhibit herding behavior in the overall market, and this tendency shows a nonlinear relationship with the market return. Nevertheless, this relationship lacks significance. The results are consistent with Ah Mand and Sifat (2021) for Malaysian conventional stocks for the overall market.

Meanwhile, the value of γ_3 in LQ45 is significantly positive (<0.05), implying that LQ45 investors did not exhibit herding behavior in the overall data. The OLS analysis produces significantly positive values of γ_3 (<0.05), but the data have heteroscedasticity problems (ARCH<0.05). In other words, there is no evidence of investors' herding behavior with a positive relationship, whether linear or nonlinear, across the entire market. The findings are consistent with Fransiska et al. (2018), who cannot document herding on LQ45 stocks.

Table 4. Herding Analysis Using DCC-GARCH (1,1) and OLS Models

		DCC-GARCH				**OLS**	**ρ-value**
		Normal	**ρ-value**	**Student's-t**	**ρ-value**		
KLCI	α	-0.0020	0.3086	0.0011	0.0000	0.0014	0.0009
	γ_2	0.1406	0.0276	0.0932	0.0000	0.4573	0.0000
	γ_3	3.6646	0.1792	-0.5259	0.5085	-2.6025	0.0958
	Vix	0.0002	0.0614	0.0001	0.2220	0.0001	0.0000
	Log-like.	7.5638		8.0911		6.9833	
	AIC	-7.7496		-8.2894		-7.1546	
	ARCH		0.7136		0.8056		0.0000
	μ_t	0.0001	0.3220	0.0001	0.0037		
	a_t	0.0940	0.0019	0.5578	0.0006		
	t-dist.	0.9297	0.0000	0.7508	0.0000		
LQ45	α	0.0073	0.0000	0.0062	0.0000	0.0031	0.0000
	γ_2	0.2589	0.0000	0.1578	0.0000	0.4557	0.0000
	γ_3	4.5869	0.0080	1.0310	0.0000	3.9490	0.0000
	Vix	-0.0002	0.0000	-0.0001	0.0000	0.0001	0.0000
	Log-like.	6.7912		6.8685		6.4444	
	AIC	-6.8945		-6.9720		-6.5451	
	ARCH		0.1405		0.1629		0.0000
	μ_t	0.0815	0.0000	0.0720	0.0000		
	a_t	0.9185	0.0000	0.9230	0.0000		
	t-dist.			3.6470	0.0000		

Source: Research finding.

Note: γ_2 represents the coefficient for the absolute market returns, γ_3 represents the coefficient for the non-linear square market returns (Eq. 5), μ_t and a_t are equation variances (Eq. 10). The best model for the Indonesian LQ45 market and the Malaysian KLCI market is the DCC GARCH (1,1) model with a Student's-t distribution.

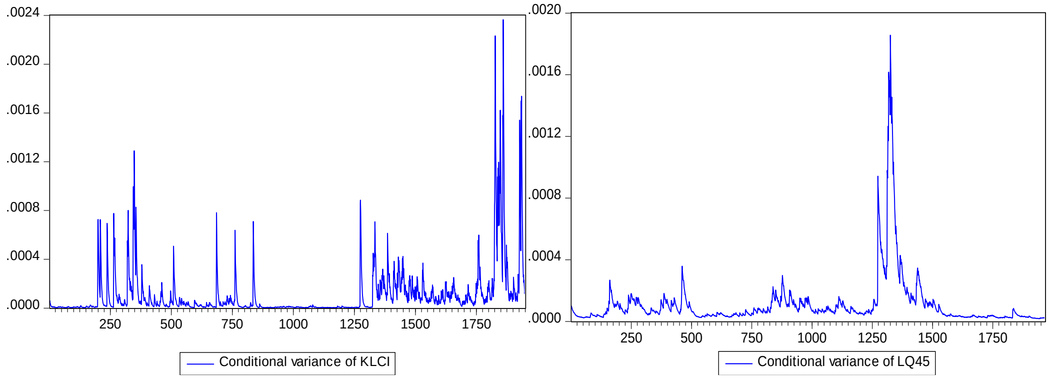

Figure 2. Graph of Conditional Variance in Overall Data
Source: Research finding.

The effect of the VIX is significantly negative in LQ45 but insignificant in KLCI, suggesting the effect of anxiety in the decision-making of LQ45 stock investors in overall observations. As previously suggested, anxious investors may make irrational decisions significantly associated with VIX and the return dispersions in the overall market. An increase in VIX is associated with lower return dispersions, implying that each investor's response tends to vary. Changes in VIX will impact investors' risk appetite for capital markets. An increase in VIX typically arises amidst a market crisis when investors sell their financial assets (Giot and Laurent, 2003). Large volatility serves as a signal for long-term investors to make buying or selling decisions.

Table 5. DCC-GARCH (1,1) and OLS in Bullish Market

		DCC-GARCH				**OLS**	**ρ-value**
		Normal	**ρ-value**	**Student's-t**	**ρ-value**		
KLCI	α	0.0019	0.0002	0.0010	0.0000	0.0017	0.0000
	γ_2	0.0766	0.0237	0.0299	0.0003	0.0672	0.0731
	γ_3	0.9181	0.0000	0.9631	0.0000	0.9271	0.0000
	Vix	-0.0001	0.7554	0.0001	0.1393	0.0001	0.3034
	Log-like.	3.9352		4.7636		3.7168	
	AIC	-8.1477		-9.8638		-7.6950	
	ARCH		0.4365		0.0318		0.0000
	μ_t	0.0001	0.1383	0.0001	0.9669		
	a_t	0.0750	0.0274	1.8851	0.9668		
	t-dist.	0.8599	0.0000	0.8207	0.0000		
LQ45	α	0.0066	0.0000	0.0054	0.0000	0.0031	0.0000
	γ_2	0.3691	0.0001	0.3129	0.0000	0.4557	0.0000
	γ_3	3.1584	0.0055	4.5578	0.0000	3.9490	0.0000
	Vix	-0.0001	0.0012	-0.0001	0.0004	0.0001	0.0000
	Log-like.	3.5135		3.5819		6.4444	
	AIC	-6.8420		-6.9736		-6.5451	

ARCH		0.2398		0.6981		0.0000
μ_t	0.0911	0.0000	0.1284	0.0002	0.0911	0.0000
a_t	0.9011	0.0000	0.8618	0.0000	0.9011	0.0000
t-dist.			3.4156	0.0000		

Source: Research finding

Note: The best model of both markets in bullish conditions is DCC GARCH (1,1) with a Student's-t distribution.

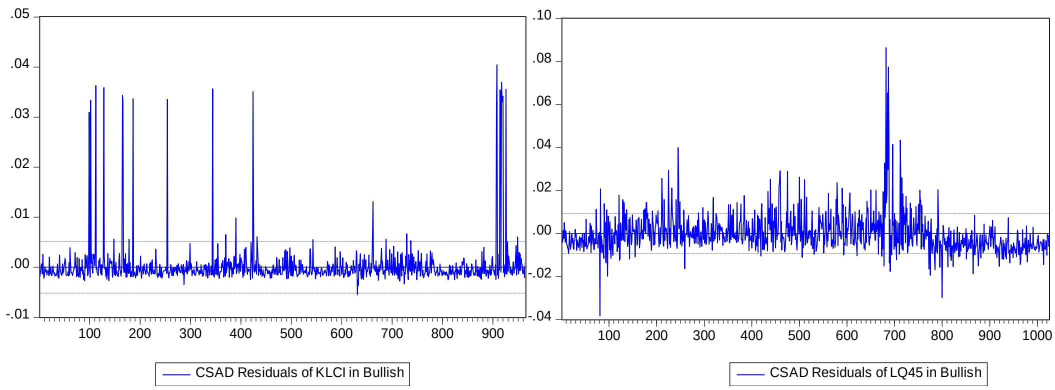

Figure 3. Graph of CSAD Residuals in Bullish Markets
Source: Research finding

Next, we investigate the level of herding behavior on days with positive market returns (bullish) using equation 6 (also available in Table 5). In both markets, in contrast to OLS, which exhibits heteroscedasticity (ARCH < 0.05), the ARCH value of GARCH (1,1) for the bullish market for overall data is greater than 0.05, indicating the absence of heteroscedasticity. The AIC value implies that the GARCH (1,1) Student's-t distribution has the smallest value and a significantly positive value of square market returns ($\gamma_3 > 0$), indicating no herding on both markets in bullish conditions. Return dispersions of CSAD do not significantly decrease during bullish market movements, indicating that herding behavior is generally unobservable among stock investors when the market prices increase. The results are consistent with Ah Mand and Sifat (2021) for Malaysian conventional stocks, demonstrating both positive linear and nonlinear relationships of the dispersion returns during bullish markets. The effect of VIX is statistically insignificant in KLCI but significantly negative in LQ45 (<0.05) in bullish conditions. The anxiety index and return dispersion exhibit a significantly negative relationship. Nevertheless, investor anxiety does not promote herding behavior at LQ45. Herding behavior is absent when investors' fear diminishes.

The GARCH (1,1) Student's-t model is utilized to analyze data from a shorter period (Table 6) in the bullish market conditions before the pandemic (2015-2019) and during the epidemic (2020-2022). According to Zhang and Giouvris (2022), herding behavior is one of the short-lived phenomena within large stock price fluctuations.

Previous research indicates that herding behavior is relatively uncommon in bullish market conditions. Table 6 displays a stable model with a positive γ_3 value in bullish markets before and during the pandemic in KLCI. Although the γ_3 value of LQ45 is negative; it is insignificant. Thus, investors in both market groups in different conditions confirm previous findings that herding does not occur over shorter periods. The effect of VIX on the dispersion of stock returns in the bullish before or during the pandemic is insignificant (>0.05).

Table 7 presents the GARCH (1,1) analysis results and compares them with the OLS models in the bearish markets of 2015-2022 using equation 7. Previous studies have demonstrated herding behavior during significant market movements or crises in the U.S. (BenSaïda, 2017).

In contrast to OLS, which exhibits heteroscedasticity ($\text{ARCH} < 0.05$), the model specification of GARCH (1,1) demonstrates heteroscedasticity-free results. The AIC value implies that GARCH (1,1) Student's-t has the smallest value. The GARCH (1,1) Student's-t model shows that both the absolute and square market returns ($\gamma_2, \gamma_3 > 0$) have significantly positive values, indicating no herding behavior in both markets during bearish conditions. Thus, investor herding behavior does not exhibit a linear or nonlinear relationship during bearish market conditions in LQ45 or KLCI. The impact of VIX on the dispersion of stock returns in bearish markets is insignificant (p-value > 0.05).

The GARCH (1,1) with Student's-t is applied to data with a shorter period (Table 8) in the bearish before the pandemic (2015-2019) and during the pandemic (2020-2022). Herding, an imitative behavior accompanied by ignoring one's beliefs, can be considered a short-term tendency. As Zhang and Giouvris (2022) suggest, herding behavior is one of the short-lived phenomena in large stock price fluctuations.

Table 6. DCC-GARCH (1,1) in Bullish Before and During the Pandemic

		Before				**During**			
	Indicator	**DCC-GARCH**	**ρ-value**	**OLS**	**ρ-value**	**DCC-GARCH**	**ρ-value**	**OLS**	**ρ-value**
KLCI	α	0.0008	0.0000	0.0013	0.0621	0.0008	0.0000	0.0016	0.0864
	γ_2	0.0298	0.0280	0.0326	0.5647	0.0547	0.0320	0.2076	0.0160
	γ_3	0.9632	0.0000	0.9615	0.0000	0.0956	0.9143	-2.6290	0.1794
	Vix	0.0001	0.0879	0.0001	0.2090	0.0001	0.2050	0.0001	0.9021
	Log-like	3.0463		2.4054		1.7217		1.3261	
	AIC	-9.9910		-7.8863		-9.6489		-7.4274	
	ARCH		0.1724		0.0286		0.4894		0.0000
	μ_t	0.0328	0.5442			8.3208	0.9998		
	a_t	0.9241	0.0000			0.5489	0.0000		
	t-dist.	2.0306	0.0000			2.0001	0.0000		
LQ45	α	0.0023	0.0358	0.0029	0.0134	0.0012	0.2732	0.0029	0.0134
	γ_2	0.8103	0.0000	0.7724	0.0000	0.0972	0.0228	0.7724	0.0000
	γ_3	-6.4531	0.1713	-5.9692	0.0177	6.0559	0.0000	-5.9692	0.0177
	Vix	0.0001	0.1327	0.0001	0.2295	0.0001	0.0692	0.0001	0.2295
	Log-like	2.2546		2.2421		1.3727		2.2426	
	AIC	-6.9586		-6.9289		-7.2014		-6.9290	
	ARCH		0.5028		0.0000	0.1457	0.0039		0.0000
	μ_t	0.1165	0.0035			0.8469	0.0000		
	a_t	0.3813	0.2770			3.8988	0.0000		
	t-dist.					0.1457	0.0039		

Source: Research finding.

Note: The table illustrates GARCH (1,1) Student's-t distribution to detect herding in bullish markets before and during the pandemic. Herding is indicated by a significantly negative value of γ_3 .

Table 7 Herding Analysis Using DCC-GARCH (1,1) and OLS in Bearish Markets

		DCC-GARCH				OLS	ρ-value
		Normal	**ρ-value**	**Student's-t**	**ρ-value**		
KLCI	α	0.0007	0.2889	0.0006	0.0001	0.0001	0.8256
	γ_2	0.9964	0.0000	0.2843	0.0000	0.9603	0.0000
	γ_3	0.0021	0.3832	0.3565	0.0000	0.0222	0.0000
	Vix	-0.0002	0.0000	-0.0001	0.0536	-0.0001	0.0000
	Log-like.	3.7455		4.6446		3.6101	
	AIC	-7.5888		-9.4123		-7.3147	
	ARCH		0.0256		0.9427		0.0000
	μ_t	0.0001	0.3920	0.0001	0.6712	0.0001	
	a_t	0.0706	0.0013	1.3886	0.6737	0.0706	
	t-dist.	0.9327	0.0000	-0.0004	0.0072	0.9327	
LQ45	α	0.0080	0.0000	0.0056	0.0000	0.0050	0.0000
	γ_2	0.1675	0.0956	0.0587	0.2336	0.2558	0.0002
	γ_3	6.1536	0.0405	1.0672	0.0000	8.4011	0.0000
	Vix	-0.0002	0.0007	-0.0001	0.0929	0.0001	0.1012
	Log-like.	3.2509		3.3043		3.1035	
	AIC	-6.8851		-6.9964		-6.5736	
	ARCH		0.4977		0.8637		0.6689
	μ_t	0.1207	0.0002	0.1117	0.0011		
	a_t	0.8820	0.0000	0.8865	0.0000		
	t-dist.			3.1622	0.0000		

Source: Research finding.

Note: A significantly negative value of γ_3 indicates herding. The best model of both markets in bearish is DCC-GARCH (1,1) Student's-t distribution.

Table 8. DCC-GARCH (1,1) in Bearish Market Before and During the Pandemic

		Before				During			
	Indicator	**DCC-GARCH**	**ρ-value**	**OLS**	**ρ-value**	**DCC-GARCH**	**ρ-value**	**OLS**	**ρ-value**
KLCI	α	0.0011	0.0000	-0.0001	0.8947	0.0006	0.0087	0.0021	0.0294
	γ_2	0.0442	0.0005	0.9834	0.0000	0.0131	0.5877	-0.2780	0.0019
	γ_3	0.4762	0.0000	0.0094	0.0439	0.0602	0.9483	1.6376	0.0000
	Vix	0.0001	0.6491	-0.0001	0.0253	0.0001	0.0001	0.0001	0.2252
	Log-like	3.0230		2.3277		1.8244		1.4214	
	AIC	-9.8496		-7.5814		-9.7601		-7.6002	
	ARCH		0.9331		0.0000		0.9462		0.0000
	μ_t	0.0501	0.9961			7.2468	0.9998		
	a_t	-0.3308	0.9202			0.3550	0.0087		
	t-dist.	2.0002	0.0000			2.0001	0.0000		
LQ45	α	0.0041	0.0010	0.0055	0.0000	0.0021	0.0722	0.0009	0.5906
	γ_2	0.6467	0.0000	0.5714	0.0000	-0.2457	0.0000	0.1212	0.2922
	γ_3	-9.4743	0.0000	-1.7036	0.5571	1.4595	0.0000	1.1076	0.0000
	Vix	-0.0001	0.9151	-0.0001	0.8485	0.0001	0.0430	0.0002	0.0005
	Log-like	2.0605		2.0092		1.3036		1.1222	
	AIC	-6.9778		-6.8088		-7.3351		-6.3177	
	ARCH		0.7359		0.0000		0.8350		0.7681
	μ_t	0.0640	0.0727			0.0001	0.1029		
	a_t	0.8460	0.0000			0.1464	0.0065		
	t-dist.	3.4631	0.0000			0.8554	.0000		

Source: Research finding.

Note: In the bearish market before and during the pandemic, the best model of FTSE KLCI or LQ45 is DCC GARCH (1,1) with a Student's-t distribution.

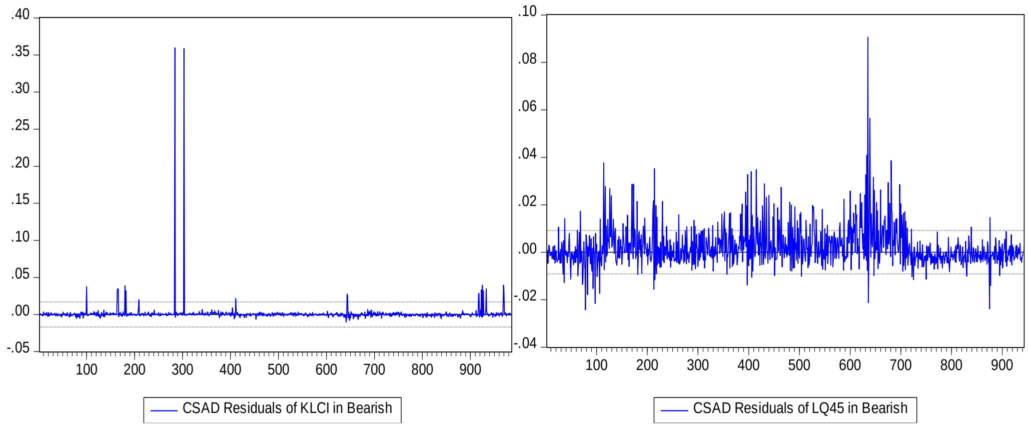

Figure 4. Graph of CSAD Residuals in Bearish Markets
Source: Research finding.

The model indicates that KLCI investors generally do not exhibit herding behavior. However, LQ45 investors indicate herding behavior before the pandemic in bearish market conditions in 2015-2019, with a significant nonlinear relationship with market returns. These results are in line with Ah Mand and Sifat (2021), who document a linear relationship between Malaysian conventional investors' herding behavior with market returns in bearish markets. The effect of VIX on bearish conditions before the pandemic is insignificant (>0.05) but significantly positive in bearish conditions during the pandemic on both indexes. Herding is a period and market variant that is not associated with market crises. Similarly, Zhang and Giouvris (2022) indicate a reciprocal relationship between the volatility index and herding unrelated to market crises due to the pandemic. The impact of the volatility index on herding is limited and transient. Furthermore, Essa and Giouvris (2023) reveal that volatility increases as investors' anxiety and uncertainty regarding the future of the economy intensify.

5. Conclusion

Our financial data exhibit heteroscedasticity-related data abnormalities. According to the kurtosis value (>3), the distributed data is leptokurtic (Kalner, 2018). As previous studies show, changes in prices and returns on securities in financial markets are not normally distributed (Chae and Lee, 2018). Statistically, the excess kurtosis should be zero for a normal distribution. OLS analysis of non-normal data will produce spurious regressions and erroneous conclusions (Gujarati and Porter, 2009). The utilization of DCC GARCH over OLS when dealing with non-normal data is crucial due to its capacity to capture time-varying volatility and correlation dynamics. Moreover, Feng and Shi (2017) contend that the Student's t distribution should be utilized instead of the normal distribution to account for the leptokurtic distribution through its specification. The DCC GARCH Student-t findings observe herding behavior in the pre-pandemic bull markets, but only for the LQ45 and not the FTSE KLCI. Thus, herding will result in lower market returns and vice versa.

Bullish markets can be defined as an optimistic anticipation concerning the future trajectory of asset prices, as evidenced by the surge in stock prices. When the outlook for a market is widely positive, individuals often tend to conform their behavior to the majority's sentiments for a sense of safety. Potential profits may induce "fear of missing out" (FOMO) among LQ45 investors. As suggested by Gupta and Shrivastava (2022), FOMO can motivate investors to "follow market consensus" and purchase assets without performing a fundamental information analysis. Herding under specific circumstances (bullish) supports the behavioral finance theory concerning irrational market behavior and should not be disregarded. Nevertheless, the impact of herding on the overall market behavior (overall/ bearish) is insignificant, suggesting that the market is efficient.

Each index comprises a collection of blue-chip stocks with solid fundamentals and performance. They are typically owned by institutional and long-term investors who engage in information-driven transactions (known as "informed trading"). Each investor has sufficient time to gather information and move independently from the others.

It is secure for investors to place their trust in blue-chip stocks with large market capitalizations, as no individual investor can influence the market consensus. Each investor behaves independently. The uneven dispersions of stock returns relative to market returns indicate the degree of independence in investment decisions. As predicted by the CAPM, the dispersions of individual market returns will diminish as the average share price movement increases (Mertzanis and Allam, 2018).

The VIX index had no significant effect on the dispersion of bullish or bearish markets before the pandemic. Nonetheless, the VIX significantly affects the bearish market during the pandemic in both indexes. The VIX coefficient exhibits a positive value during pandemic-driven extreme market conditions. A rise in the VIX is associated with an increase in the dispersion of returns (CSAD). Hence, each investor's response increases as the VIX index increases. Changes in the VIX will affect investors' risk appetite for the stock market. VIX frequently increases during financial crises as investors overreact by selling their financial assets to limit losses (Giot and Laurent, 2003).

This paper empirically examines time-varying herding through the DCC-GARCH model and tests daily herding by including a volatility index variable before and during the pandemic. This model has reliable forecasting capabilities, especially from multi-frequency data sets. This paper offers a potential contribution by further elucidating the relationship between beta and volatility in the context of herding behavior. In this respect, herding is a fluid phenomenon that fluctuates over time. The results differ from Hsieh (2013), who documents that small-share investor groups employing a feedback strategy are more prevalent in markets with greater pressure. Beta herding becomes a factor when portfolio movements are extreme or markets are volatile.

Our research results are important for investors. For example, the size of beta herding for systematic risk factors can be adjusted regarding portfolio allocation. Blue-chip portfolio policies are also important to reduce losses due to investor herding. Future research could expand the model to clustering volatility or leverage effects. It might be better to use other models, such as the EGARCH, QGARCH, and GJR GARCH, that capture the asymmetry in the conditional variances. In addition, macroeconomic and fundamental factors dynamics can be used as a proxy for time-varying beta.

Statements and Declarations

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- Conflicts of Interest Statement: The authors have no conflicts of interest to declare.

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