Original Article

Herding Behaviour in ESG Stock Index: Evidence from Emerging Markets

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Abstract

This article studies the herding behaviour of environmental, social and governance stock indices in the emerging market based on International Monetary Fund emerging market criteria. We use the daily data as a sample. Cross-sectional absolute deviation is employed to identify the herding behaviour of the investors. The findings report that all the indices do not exhibit herding behaviour, even under the upwards and downwards episodes of the market. When oil price and implied volatility are included in the model, the herding only existed in some samples, such as Egypt and India, during upwards oil price fluctuation and implied volatility, respectively. Meanwhile, Brazil, China and Taiwan also show evidence of herding behaviour during downwards oil price fluctuation. It is due to the large size of the companies with solid governance norm included in the indices, and the information on the companies are widely available. It gives the implication that the investors do not rely on others in the investment decision.

Keywords

Emerging markets, ESG, herding behaviour, implied volatility, oil price

Introduction

The ability to assess environmental, social and governance (ESG) performance has become just as important as tracking profit and loss due to the increased awareness of ESG issues and because it is recognized that the two are permanently linked. When episodes in the market create highly uncertain environments, traders have to evaluate the impacts on their portfolios. As studies show that the financial crises, bubbles and stock collapses were all caused by the herding tendency in the financial markets, for example, Armansyah (2018) stated that herd behaviour contributed to the dot-com disaster, the financial crisis and stock market crashes in Asia (1997–1998), Argentina (2000–2006) and other regions (2008–2009). Until now, researchers have been looking at the traders' reactions from two approaches—efficient market hypothesis and herding behaviour (market sentiment). Most studies focus on the herding behaviour of conventional and Islamic stock markets. For example, Raut et al. (2020), Aloui et al. (2021), Nor et al. (2013), Ah Mand et al. (2023), Danila et al. (2021), Eki Rahman and Ermawati (2020), Jiranyakul (2007), Khanthavit (2019), Nor et al. (2013) and Rashid et al. (2014) reported that some

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Association of Southeast Asian Nations (ASEAN) markets are driven by investor sentiment. Uygur and Taş (2014) presented evidence on market sentiment in major developed markets by using residuals of weekly trading volumes as a proxy for investor sentiment. Other studies also demonstrated the significant relationship between market sentiment (herding behaviour) and stock return volatility, few to mention are Baker et al. (2012), Lee (2019), Mujtaba Mian and Sankaraguruswamy (2012) and Rupande et al. (2019).

Individual and institutional investors include ESG as one of the crucial considerations in investing their wealth. ESG investing has developed in recent years to meet the demands of individual and institutional investors and some public sector regulators who want to more effectively incorporate long-term financial opportunities and risks into their investment decision-making processes to create long-term value. In these circumstances, a rising need exists among different types of investors to strengthen portfolio alignment with societal objectives, such as reducing climate change, fostering ethical behaviour and ensuring high standards of corporate governance. ESG disclosure is becoming increasingly popular because it may be a valuable tool for issuers to examine and report their socially responsible actions and investors seeking to evaluate the possibility of social returns across enterprises and over time (Al-Hiyari & Kolsi, 2021; Boffo & Patalano, 2020). The phenomenon above raises the question of whether investors act similarly to those participating in conventional stock markets. Few studies have been conducted to address this subject, such as Vuong and Suzuki (2020) investigated the role of market sentiment on ESG performance in Japan. The authors revealed that the company's commitment towards its ESG activities depends on the negative sentiment in the past. Furthermore, Rubbaniy et al. (2021) reported a significant herding behaviour in the US ESG leader stocks during all market conditions.

Nonetheless, a study on herding behaviour on ESG stock indices in the emerging market is yet to be conducted. As Balakrishnan et al. (2013) indicated, emerging markets become attractive investment places for international investors due to extra liquidity. Emerging market values are low when compared to developed market stocks on a price-to-earnings (P/E) and price-to-book (P/B) basis (Outlook on Emerging Markets, 2023). Emerging market policies have usually been less unconventional and stable than those of developed markets, resulting in stronger economies than their unique history and those of advanced countries. Emerging markets provide chances for stock investors in high-quality, fast-growing firms. They are home to some of the world's most cutting-edge, tech-focused businesses, creating the digital infrastructure that surrounds us (Ness, 2022).

By investigating the investors' behaviour of ESG indices in the emerging market, we are interested in finding out whether their behaviour is identical to that of the investors in developed countries since these investors are long-term investors who expect long-term growth of the companies instead of capital gain from the daily buying and selling securities.

Our article differs from previous research in the following ways. We used ESG stock indexes of emerging markets, and the article is the first study to analyse herding behaviour in the ESG stock indexes of the emerging markets. We also included the global factors in our analysis, as suggested by Economou et al. (2015) and Indārs et al. (2019). This study has practical value for various stakeholders, such as investors and fund managers, to make investment selections, including their portfolio diversification and risk management techniques. The behaviour shows how market participants make decisions regarding selling and buying ESG securities, which affects their portfolio return and eventually may cause a financial crisis. Moreover, understanding the investors' behaviour in the stock markets enables regulators to overcome the potential risks related to this action, thereby assuring the financial and economic stability of the financial market.

By doing so, we provide a fresh insight and improve the body of literature by providing no evidence of herding behaviour in the emerging market ESG stock indices under normal, rising and declining markets. Oil price fluctuation and implied volatility do not have any role in the herding behaviour in most samples. Only two markets show the behaviour when upside fluctuation of oil price and implied volatility exists—Egypt and India, respectively; three markets—Brazil, China and Taiwan—exhibit behaviour when there is downside volatility of oil price.

The rest of the article is organized as follows. The next section describes the literature review. We present the study's data and methods in the subsequent section. The discussion and recommendations based on the data's analysis are elaborated next. The conclusion, which highlights the applicability of our findings, is presented in the last section.

Literature Review

Rational traders act rationally by maximizing expected utility while maintaining reasonable expectations for the future value of risky assets. Thus, rationality consists of two entities: when investors obtain information, they will correctly update their views and make appropriate decisions based on their beliefs. According to behavioural theorists, investors are not rational, and irrational investors are known as 'noise traders' (Barberis & Thaler, 2003). These irrational participants contribute mainly to market volatility caused by market emotion (Baker & Wurgler, 2006). Moreover, Baker et al. (2012) indicated that global and local sentiment are the factors in predicting the market returns of a contrarian. Greenwood and Shleifer (2014) also proved the evidence of investors' irrational behaviour due to the negative correlation between investor expectations and model-based expected returns. Kim et al. (2014) concludes the same result that the sentiment of investors significantly affects the predictability of stock market return.

With regard to the herd behaviour, Bikhchandani and Sharma (2000) differentiate the behaviour into spurious and intentional herding. Spurious herding is when inventors make similar trading due to possessing the same fundamental information. In the meantime, intentional herding is when the traders follow others in trading intentionally. Some researchers focus on institutional investors, such as, Arouri et al. (2013), Lakonishok et al. (1992), Oran and Cobandag (2021), Ramli et al. (2016), Sonaer et al. (2011) and Stein et al. (2020), whilst others study the herding towards a consensus of the market by using the whole market data such as. Chang et al. (2000), Galariotis et al. (2016) and Indārs et al. (2019 Choi and Skiba (2015) suggested that the herding in the international market is expansive, and there is evidence of spurious herding. The investors analyse the information in the same way and have similar decisions from the fundamental facts, especially when the markets provide a transparent report. Results show that the observed herding is price stabilization rather than irrational actions. By contrast, Galariotis et al. (2016) found no herding behaviour in the US and UK markets using a total sample, even after examining the possibility of asymmetries such as days with positive returns (up days) and negative returns (down days). The authors add macroeconomics announcement, but the result is the opposite. Spurious herding behaviour seems compelling for US investors. The announcement revises the investors' beliefs and preferences for stock valuation. Fundamental and non-fundamental information also bring herding at the time of the Asian and Russian crises, and the Subprime crisis. Similarly, Arjoon et al. (2020) show evidence of spurious and intentional herding at the market level and large portfolios; only intentional herding is prevalent for small portfolios. Liquidity, volatility and upmarket conditions increase herding behaviour at the market level and in all portfolio sizes. However, Holmes et al. (2013) provided evidence of the intentional herding behaviour of institutional investors by using monthly holdings data for Portugal. Reputational factors drive the behaviour. Gavriilidis et al. (2013) came to the same conclusion of intentional herding by Spanish portfolio managers, especially during underperformed markets.

Asymmetry of Herding—Return and Volatility

Empirical research on the correlation between market performance—up- and down market—yield mixed results. Chiang et al. (2013) suggested that both rising and declining markets exhibit herding. It is significant that the degree of herding changes throughout time. By using the implied volatility index (VIX) based on S&P500 options (CBOE VIX) as a proxy of volatility, the authors discover that herding has a positive correlation with stock returns but a negative correlation with market volatility. Positive correlations between herding estimates across markets indicate that investor behaviour in the area is moving in perfect sync.

Mobarek et al. (2014) argued that herd behaviour is not substantial in Europe during normal times. However, it is significant during crises and in regimes of extreme market situations, according to a comparative country-by-country examination of European nations. During asymmetric market circumstances and times of crises, there are strong herding coefficients, although these vary among nation groups. The study also comes to the conclusion that common herding forces exist in many European marketplaces and are closely connected among markets of a similar nature. Asymmetric herding effects have been observed on days when the return of the market is down (Philippas et al., 2013).

Oil Price and Herding

Numerous empirical evidence shows a positive correlation between oil price and stock market return, such as Aggarwal and Manish (2020) and Wang et al. (2013) concluded that oil price changes have a more significant and long-lasting impact on the stock market for oil-importing nations. It also demonstrated that positive aggregate and precautionary demand shocks increase stock market co-movement amongst oil-exporting countries but not those in oil-importing nations. Regarding herding, Demir and Solakoglu (2016) reported that oil returns and their volatility drive stock herding behaviour in Qatar. Balcilar et al. (2014) exhibited evidence of herding in all Gulf Arab stock markets. The oil price as a global factor is critical to the transition to herding states. Indārs et al. (2019) suggested that herding behaviour exists during large oil price movements in the Russian market, which is frequently seen in bullish markets. By contrast, herding behaviour does not exist during downwards movements in oil prices. The controlled oil companies by the government might be the reason for the asymmetric behaviour.

Data and Methods

We use ESG indices of the emerging market as data samples for the analysis. Table 1 shows the details of the data. The global factors include the West Texas Intermediate (WTI) oil price and the VIX. Crude oil price and VIX are used as indicators for influencing the dynamics of global financial markets (Chiang et al., 2013; Economou et al., 2015; Indārs et al., 2019; Philippas et al., 2013). All data are obtained from

Table 1. Data and Periods.

Index	Period
MSCI Brazil ESG	29 March 2017–15 April 2022
MSCI China Carbon SRI leaders	01 September 2020–18 April 2022
S&P/ESG Egypt	26 July 2018–21 April 2022
SRI Kehati (Indonesia SRI)	29 March 2017–18 April 2022
MSCI India ESG	29 March 2020–15 April 2022
MSCI Malaysia ESG Leaders	29 March 2017–15 April 2022
MSCI Thailand	29 March 2017–15 April 2022
MSCI Taiwan ESG Leaders	29 March 2017–15 April 2022
MSCI South Africa ESG Leaders	29 March 2017–15 April 2022

Source: Bloomberg and Yahoo Finance sites.

Note: Each index's latest five-year periods are considered enough to conduct the herding behaviour test. MCI China, MCI Egypt and MCI India were established later than the rest of the indices.

Bloomberg and Yahoo finance sites. For each index, we use 10 top constituents; it covers around 65–77% of the total market index. Except for Indonesia and Egypt indices, we use all stocks.

Cross-sectional Absolute Deviation Model

We follow Chang et al. (2000) to measure herding by calculating cross-sectional absolute deviation (CSAD), which is widely used and more robust than cross-sectional standard deviation (CSSD) in detecting herding behaviour amongst investors in the stock market.

$$CSAD_t = \frac{1}{N}\Sigma_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right| \tag{1}$$

where $CSAD_t$ is the portfolio return absolute deviation; N is the number of portfolio's stocks; $R_{i,t}$ is the stock I return at time t; $R_{m,t}$ is a return of stock index at time t.

The next step is to regress the average market return to CSAD. The model is as follows:

$$CSAD_t = \alpha + \beta_1\left|R_{m,t}\right| + \beta_2\ R_{m,t}^2 + \varepsilon_t \tag{2}$$

where α is an intercept; β_1 and β_2 are loadings of $|R_{m,t}|$ (absolute cross-sectional average returns) and $R^2_{m,t}$ (squared cross-sectional average returns), respectively; ε_t is the error term. Herding behaviour is present when β_2 is a significantly negative value as market consensus states that the non-linearity relationship between $CSAD_t$ and $R^2_{m,t}$ must be captured when the market is herd during the market swings episodes.

To handle the serial correlation issue, Arjoon et al. (2020) includes $CSAD_{t-1}$ in Equation (3):

$$CSAD_t = \alpha + \beta_1 \left|R_{m,t}\right| + \beta_2 R_{m,t}^2 + \beta_3 CSAD_{t-1} + \varepsilon_t \tag{3}$$

Furthermore, we study whether the herding is asymmetric during the episodes of up- and down markets. Following, Indārs et al. (2019), we split the sample into two (up- and down market) and estimate each model as follows:

$$CSAD_t = \alpha + \beta_1 D_u \left|R_{m,t}\right| + \beta_2 D_u R_{m,t}^2 + \beta_3 CSAD_{t-1} + \varepsilon_t \tag{4}$$

$$CSAD_t = \alpha + \beta_1 D_d \left|R_{m,t}\right| + \beta_2 D_d R_{m,t}^2 + \beta_3 CSAD_{t-1} + \varepsilon_t \tag{5}$$

where $D_u = 1$ if $R_{m,t} > 0$, and 0 otherwise; and $D_d = 1$ if $R_{m,t} < 0$, and 0 otherwise. A negative and statistically significant β_2 coefficient means market herd during up- or down episodes.

Next, we observe global factors affecting market herd behaviour. We include oil price and VIX as proxies of global variables.

$$CSAD_t = \alpha + \beta_1 \left|R_{m,t}\right| + \beta_2 R_{m,t}^2 + \beta_3 D_{u,oil} R_{m,t}^2 + \beta_4 D_{u,vol} R_{m,t}^2 + \beta_5 CSAD_{t-1} + \varepsilon_t \tag{6}$$

$$CSAD_t = \alpha + \beta_1 \left|R_{m,t}\right| + \beta_2 R_{m,t}^2 + \beta_3 D_{d,oil} R_{m,t}^2 + \beta_4 D_{d,vol} R_{m,t}^2 + \beta_5 CSAD_{t-1} + \varepsilon_t \tag{7}$$

where $D_{u,\ oil} = 1$ on days when a difference in oil prices within the top 5th percentile, and 0 otherwise. $D_{u,vol} = 1$ on days when a difference in volatility within the top 5th percentile, 0 otherwise. $D_{d,oil} = 1$ on days when a difference in oil prices within the bottom 5th percentile and 0 otherwise. $D_{d,vol} = 1$ on days when a difference in volatility within the bottom 5th percentile, 0 otherwise.

Quantile regression is proposed in the next part to analyse the consistency of the outcome. It is an effective method for finding herding behaviour at market distribution extremes, that is, identifying herding in other areas when market distribution is analysed.

Quantile Regression Model

The quantile regression model calculates the connection between the dependent and explanatory variables by applying the model to various quantiles. The method is more robust to outliers because it takes all possible data points that could be observed from the model into account. The model is as follows (Ampofo et al., 2023):

$$y_i = Q_\tau\left(Y|X = x\right) = x_i' \gamma^* \tag{8}$$

where y_i and x_i are dependent and vector of independent variables consecutively, and γ^* is a vector of the quantile regression parameters. The median absolute deviation is shown in Equation (9):

$$MAD = \frac{1}{n} \Sigma_{i=1}^{n} \rho_\tau \left(y_i - x_i' \gamma^*\right) \tag{9}$$

Table 2. Summary Statistics of CSAD and Returns of Indices (R_m).

	CSAD				Rm			
Index	Mean	*SD*	Skewness	Ex. kurtosis	Mean	*SD*	Skewness	Ex. kurtosis
MSCI Brazil ESG	0.0150	0.0075	2.2993	9.1138	0.0002	0.0235	−0.6847	7.8360
MSCI China Carbon SRI Leaders	0.0183	0.0083	2.1683	12.110	−0.0006	0.0216	1.0008	9.6410
S&P/ESG Egypt	0.0174	0.0084	5.4474	67.397	−0.0004	0.0166	−1.8851	13.136
SRI Kehati (Indonesia)	0.0152	0.0055	2.2639	11.388	0.0002	0.0140	0.8408	16.549
MSCI India ESG	0.0106	0.0041	1.3772	3.2536	0.0007	0.0111	−0.3515	1.4229
MSCI Malaysia ESG Leaders	0.0092	0.0049	2.1336	8.4985	0.0001	0.0088	−0.2649	7.6520
MSCI Thailand	0.0099	0.0050	3.1585	19.451	0.0001	0.0112	−1.1182	19.072
MSCI Taiwan ESG Leaders	0.0106	0.0049	1.9346	8.4342	0.0009	0.0128	−0.1028	3.7548
MSCI South Africa ESG Leaders	0.0184	0.0102	2.4300	9.6869	0.0003	0.0195	−0.5103	3.0446

The function ρ is the check function which gives asymmetric weights to the error depending on the quantile and the overall sign of the error. ρ takes the following form:

$$\rho_\tau(u) = \tau \max(u,0) + (1-\tau)\max(-u,0) \tag{10}$$

The $CSAD_t$ model in Equations (3)–(7) is expressed in quantile as

$$CSAD_{t,\tau} = \alpha + \beta_{1,\tau}\left|R_{m,t}\right| + \beta_{2,\tau}R^2_{m,t} + \beta_{3,\tau}CSAD_{t-1} + \varepsilon_t \tag{3'}$$

$$CSAD_{t,\tau} = \alpha + \beta_{1,\tau}D_u\left|R_{m,t}\right| + \beta_{2,\tau}D_uR^2_{m,t} + \beta_{3,\tau}CSAD_{t-1} + \varepsilon_t \tag{4'}$$

$$CSAD_{t,\tau} = \alpha + \beta_{1,\tau}D_d\left|R_{m,t}\right| + \beta_{2,\tau}D_dR^2_{m,t} + \beta_{3,\tau}CSAD_{t-1} + \varepsilon_t \tag{5'}$$

$$CSAD_{t,\tau} = \alpha + \beta_{1,\tau}\left|R_{m,t}\right| + \beta_{2,\tau}R^2_{m,t} + \beta_{3,\tau}D_{u,oil}R^2_{m,t} + \beta_{4,\tau}D_{u,vol}R^2_{m,t} + \beta_{5,\tau}CSAD_{t-1} + \varepsilon_t \tag{6'}$$

$$CSAD_{t,\tau} = \alpha + \beta_{1,\tau}\left|R_{m,t}\right| + \beta_{2,\tau}R^2_{m,t} + \beta_{3,\tau}D_{d,oil}R^2_{m,t} + \beta_{4,\tau}D_{d,vol}R^2_{m,t} + \beta_{5,\tau}CSAD_{t-1} + \varepsilon_t \tag{7'}$$

The herding behaviour was estimated at 25%, 50% and 75% quantiles. Negative and statistically significant of $\beta_{2,\tau}$ in Equations (3'), (4') and (5'); $\beta_{2,\tau}$, $\beta_{3,\tau}$ and $\beta_{4,\tau}$ in Equations (6') and (7') indicate the herding behaviour.

Empirical Findings

Table 2 describes the main statistics of R_m and CSAD for all indices. The mean values for all series of *CSAD* and R_m are close to zero. On average, the CSAD of all series has a smaller standard deviation than the R_m series in which Brazil's index return places the highest. The skewness of both variables indicates deviating from the normal distribution curve, that is, beyond the range of -0.5–0.5. Only Malaysia's index return shows a relatively symmetrical curve. All signs of CSAD's skewness are positive, which meant that the value of CSAD is less than average. However, most of the indices' return is negative; the indices' return value is more than average. *CSAD* and R_m data exhibit leptokurtic distributions, indicating that the data have significant outliers. Only India reports platykurtic distribution, that is, light outliers.

Table 3 summarizes the results of Equations (3)–(7) for all indices regarding herding towards the market. The first three models present significant and positive values of β_2. There is no evidence of the herding behaviour of the investors. The findings contradict some previous studies; for example, Arjoon et al. (2020), Choi and Skiba (2015), Gavriilidis et al. (2013) and Holmes et al. (2013), which show herding behaviour in the markets. Nevertheless, the finding is supported by other studies, such as Bikhchandani and Sharma (2000), Galariotis et al. (2016) and Indārs et al. (2019). Money managers who trade for large companies do not show herding behaviour, however the behaviour has existed for small companies. The reason is that small companies carry less public information, which induces the money managers to provide further intention to other investors' actions in deciding their own investment (Bikhchandani & Sharma, 2000). Furthermore, according to Chen et al. (2020), the herding tendency was evident due to a lack of knowledge or familiarity with the circumstance and to actions taken in a similar circumstance in the past. Investors who follow other investors tend to believe they are more capable of evaluating the best investment options and making decisions because of their ignorance. As in our samples, all of them are large companies that met the ESG requirements. Then, non-herding behaviour is expected in the indices. Furthermore, Moscow market investors do not show herding behaviour based on market-wide and fundamental factors (Indārs et al., 2019). We reach the same conclusion when we separate up- and down-market periods (asymmetric factor) on herding, that is, no herding behaviour for all samples. The result is consistent with Gleason et al. (2004), who suggested that investors do not reveal herding behaviour during periods of extreme up market and down market in exchange-traded funds (ETFs). Effective information dissemination eliminates the need for traders to rely on their trading decisions on apparent consensus behaviour.

The next step is to include the global factors—oil price and implied volatility—in the model. We further distinguish two extremes of up- and down fluctuation on the oil price and implied volatility variables. The results are mixed. First, all samples show no evidence of herding in the period of upwards fluctuation of the oil price and volatility, except Egypt, which exhibits herding during an upwards market period of implied volatility, and India experiences herding during the upwards market period of oil price. Second, only China and Taiwan ESG indices have herded during a down period of oil prices, whilst Brazil has the same phenomenon during both downwards periods of oil prices and implied volatility. The rest of the samples do not exhibit investors herding behaviour, that is, all loadings are either significantly positive or insignificantly negative. The finding is consistent with Eki Rahman and Ermawati (2020). The authors reported no herd behaviour due to oil swing price fluctuation. Some of the results above confirm the previous studies; for example, the Moscow market exhibits herding behaviour during upwards oil price fluctuation (Indārs et al., 2019). Demir and Solakoglu (2016) concluded that oil returns and their volatility drive stock herding behaviour in Qatar. Chiang et al. (2013) also reported herd behaviour in the US market due to implied volatility. The investors in the ESG stock indices in emerging

Table 3. Estimates of Herding Behaviour with All Models.

Variables	Brazil	China	Egypt	Indonesia	India	Malaysia	Thailand	Taiwan	*South Africa*
Model 1: $CSAD_t = \alpha + \beta_1 \left\|R_{m,t}\right\| + \beta_2 R^2_{m,t} + \beta_3 CSAD_{t-1} + \varepsilon_t$									
A	0.0079	0.0127	0.0116	0.0093	0.0079	0.0041	0.0060	0.0059	0.0078
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	0.2335	0.1825	0.4002	0.1897	0.1765	0.4271	0.2134	0.2672	0.3118
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0462)**	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_2	0.2631	1.5443	−0.0275	0.0072	−1.7402	0.5336	0.7491	0.7252	0.7317
	(0.5074)	(0.0000)***	(0.9803)	(0.9782)	(0.6073)	(0.5788)	(0.4138)	(0.6307)	(0.6136)
β_3	0.2099	0.1176	0.0861	0.2701	0.1408	0.2668	0.2270	0.1978	0.3165
	(0.0000)***	(0.0039)***	(0.1101)	(0.0000)***	(0.0027)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
Model 2: $CSAD_t = \alpha + \beta_1 D_u \left\|R_{m,t}\right\| + \beta_2 D_u R^2_{m,t} + \beta_3 CSAD_{t-1} + \varepsilon_t$									
A	0.0094	0.0142	0.0137	0.0096	0.0089	0.0049	0.0060	0.0073	0.0104
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	0.0913	0.1644	−0.05390.3340	0.1978	−0.0838	0.2139	0.2134	0.07890.2139	−0.0214
	(0.0020)***	(0.0010)***		(0.0000)***	(0.4150)	(0.0000)***	(0.0000)***		(0.7580)
β_2	1.96217	1.62796	8.4693	0.2619	8.4791	4.8847	0.7491	4.8592	6.2852
	(0.0112)**	(0.0000)***	(0.0000)***	(0.2471)	(0.1365)	(0.0004)***	(0.4138)	(0.0919)*	(0.0010)***
β_3	0.287142	0.140257	0.1877	0.3085	0.1462	0.3777	0.2270	0.2350	0.3809
	(0.0000)***	(0.0017)***	(0.0063)***	(0.0000)***	(0.0019)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
Model 3: $CSAD_t = \alpha + \beta_1 D_d \left\|R_{m,t}\right\| + \beta_2 D_d R^2_{m,t} + \beta_3 CSAD_{t-1} + \varepsilon_t$									
A	0.0096	0.0144	0.0131	0.0093	0.0089	0.0049	0.0065	0.0073	0.0107
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
β_1	0.0189	−0.154466	0.2381	0.0172	0.1044	0.0985	0.0419	0.02894	0.0464
	(0.5138)	(0.0081)***	(0.0006)***	(0.7605)	(0.1803)	(0.0295)**	(0.2622)	(0.5238)	(0.4990)
β_2	1.3895	5.39734	0.9762	0.0603	−1.6683	4.8885	1.3244	3.2940	3.1377
	(0.0083)***	(0.0000)***	(0.4424)	(0.9755)	(0.5613)	(0.0005)***	(0.0117)**	(0.0440)**	(0.0727)*
β_3	0.3249	0.218502	0.1608	0.3885	0.1364	0.4097	0.3141	0.2757	0.3661
	(0.0000)***	(0.0000)***	(0.0335)**	(0.0000)***	(0.0047)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***

(Table 3 Continued)

(Table 3 Continued)

	Model 4: $CSAD_t = \alpha + \beta_1 \left\| R_{m,t} \right\| + \beta_2 R^2_{m,t} + \beta_3 D_{u,oil}\ R^2_{m,t} + \beta_4 D_{u,vol}\ R^2_{m,t} + \beta_5 CSAD_{t-1} + \varepsilon_t$								
A	0.00781794 (0.0000)***	0.0126 (0.0000)***	0.0126 (0.0000)***	0.0090 (0.0000)***	0.0081 (0.0000)***	0.0041 (0.0000)***	0.0063 (0.0000)***	0.0061 (0.0000)***	0.0079 (0.0000)***
β_1	0.1820 (0.0000)***	0.1915 (0.0000)***	0.1500 (0.2220)	0.2008 (0.0000)***	0.1381 (0.0984)*	0.4222 (0.0000)***	0.1983 (0.0121)**	0.1817 (0.0004)***	0.3167 (0.0000)***
β_2	−0.04580 (0.9161)	1.742(0.4616)	4.7509 (0.0000)***	−0.0418 (0.9772)	16.5143 (0.1303)	−1.4579 (0.2893)	−5.0301 (0.3264)	−2.2788 (0.1804)	−0.2500 (0.9002)
β_3	1.3301 (0.0000)**	1.3456 (0.0095)***	5.4893 (0.1234)	1.1841 (0.2570)	−12.2085 (0.0720)*	−0.0050 (0.9977)	0.8029 (0.7612)	4.0458 (0.0048)***	−0.0446 (0.9666)
β_4	0.6464 (0.0202)**	−1.5131 (0.4932)	−3.8449 (0.0000)**	−1.0900 (0.4645)	−5.3617 (0.4482)	2.4520 (0.1866)	5.8396 (0.2085)	2.7917 (0.1428)	0.9560 (0.4863)
β_5	0.221381 (0.0000)***	0.1152 (0.0044)**	0.1084 (0.0175)**	0.2777 (0.0000)***	0.1448 (0.0025)***	0.2639 (0.0000)***	0.2320 (0.0000)***	0.1987 (0.0000)***	0.3160 (0.0000)***
	Model 5: $CSAD_t = \alpha + \beta_1 \left\| R_{m,t} \right\| + \beta_2 R^2_{m,t} + \beta_3\ D_{d,oil}\ R^2_{m,t} + \beta_4 D_{d,vol}\ R^2_{m,t} + \beta_5 CSAD_{t-1} + \varepsilon_t$								
A	0.00781795 (0.0000)***	0.0126 (0.0001)***	0.0125 (0.0000)***	0.0090 (0.0000)***	0.0081 (0.0000)***	0.0041 (0.0000)***	0.0063 (0.0000)***	0.0061 (0.0000)***	0.0079 (0.0000)***
β_1	0.1820 (0.0000)***	0.1915 (0.0001)***	0.1500 (0.2220)	0.2008 (0.0000)***	0.1381 (0.0984)*	0.4222 (0.0000)***	0.1983 (0.0121)**	0.1817 (0.0004)***	0.3167 (0.0000)***
β_2	1.5186 (0.0000)***	1.5751 (0.0001)***	6.3953 (0.1591)	0.0522 (0.7950)	−1.0559 (0.7470)	0.9890 (0.6815)	1.6124 (0.6412)	4.5587 (0.0260)	0.6613 (0.7028)
β_3	−1.3301 (0.0000)***	−1.3456 (0.0095)***	−5.4893 (0.1234)	−1.1841 (0.2570)	12.2085 (0.0720)	0.0050 (0.9977)	−0.8029 (0.7612)	−4.0458 (0.0048)***	0.0446 (0.9666)
β_4	−0.6464 (0.0212)**	1.5131 (0.4932)	3.8449 (0.0000)***	1.0900 (0.4645)	5.3617 (0.4482)	−2.4520 (0.1866)	−5.8396 (0.2085)	−2.7918 (0.1428)	−0.9560 (0.4863)
β_5	0.221380 (0.0000)***	0.115621 (0.0044)***	0.1084 (0.0175)**	0.2777 (0.0000)***	0.1448 (0.0025)***	0.2639 (0.0000)***	0.2320 (0.0000)***	0.1987 (0.0000)***	0.3160 (0.0000)***

Notes: Sig-values are in parentheses. *10% level of significance; **5% level of significance; ***1% level of significance. Model 1 is the original model, which investigates the presence of herd behaviour. Models 2 and 3 investigate the asymmetric herding behaviour when the market is at up and down episodes, where D_u = 1 if $R_{m,t}$ > 0, and 0 otherwise, and D_d = 1 if $R_{m,t}$ < 0, and 0 otherwise. Models 3 and 4 incorporate global factors, namely oil price and volatility, where D_u*oil* = 1 on days when a movement in oil prices within the top 5th percentile and 0 otherwise. D_u*vol* = 1 on days when a movement in volatility within the top 5th percentile, 0 otherwise. D_d*oil* = 1 on days when a movement in oil prices within the bottom 5th percentile and 0 otherwise. D_d*vol* = 1 on days when a movement in volatility within the bottom 5th percentile, 0 otherwise. We used HAC robust standard errors (Huber-White standard errors), which are robust in the presence of heteroscedasticity (and, in the case of the HAC estimator, autocorrelation).

markets are not herding. However, only a few indices show the behaviour when we include oil price and implied volatility as global factors in the model.

According to theoretical and empirical research, herding may occur in equity markets when a lack of knowledge about financial assets exists. Furthermore, the reasons for ESG indices not showing herding behaviour in the emerging market are as follows. First, ESG indices consider a variety of criteria, such as board composition, labour practices, carbon emissions and others. Each index may have its own set of criteria and weightings, resulting in differences in the company composition. Industries such as energy, resources or finance are frequently more concentrated in emerging economies. Compared with prominent sectors in developed economies, these industries may face various ESG concerns and challenges. Because of this diversity, it is less probable that all investors will agree on the same ESG equities, minimizing the possibility of herding. Second, ESG preferences and priorities vary across investors. Whilst some investors may prioritize social or governance issues, others may pay greater attention to environmental problems. This difference further reduces the likelihood of herding behaviour in preferences. Third, emerging market dynamics and risk considerations are frequently unique and may affect investing choices. Political unrest, currency swings and problems with governance can all significantly impact investment decisions. As a result, there may be less herding behaviour in ESG indexes among investors in developing markets who value these variables above ESG concerns. Fourth, ESG investment is still beginning in numerous developing countries, and investor knowledge of sustainable investing techniques may be comparatively poor. Investors might need to be more knowledgeable about ESG perspectives or completely comprehend the possible advantages and challenges of ESG investment. This lack of understanding may lessen investors' likelihood to follow ESG indices and exhibit herding behaviour. Fifth, ESG indexes generally choose and weigh equities based on rules. Active managers and investors could diverge from the index composition if they have specific ESG strategies and viewpoints. Active management increases the variety of ESG investing strategies, lowering herding behaviour likelihood. Finally, ESG investment frequently places its attention on long-term sustainability and ethical behaviour. This emphasis on long-term factors may encourage investors to take independent positions, rather than just following the herd by focusing their selections on evaluating a company's ESG performance and prospects for sustainable growth.

Quantile Regression Estimates

Quantile regression results are presented in Table 4. Most results are consistent with the previous CSAD model, which is no herding behaviour. However, few show different results; for example, there is evidence of herding when the oil price is at upside fluctuation in Malaysia and South Africa at the lowest quantile (25%). The herding also is revealed when there is downside fluctuation of oil prices in Thailand, Taiwan and India at 25%, 50% and 75%, respectively. Thus, the herding is only prevalent in the specific area of a return distribution.

Conclusion

As demand rises for sustainable investing solutions, not only in the developed markets but sustainability funding is also ultimately required in emerging markets. Hence, the firms in emerging markets compete with the developed markets with regards to ESG issues. The stock market started to develop an index

Table 4. Quantile Regression Herding Behaviour with All Models.

Variables	Brazil	China	Egypt	Indonesia	India	Malaysia	Thailand	Taiwan	South Africa
Model 1: $CSAD_{t,\tau} = \alpha + \beta_{1,\tau}\left|R_{m,t}\right| + \beta_{2,\tau}R^2_{m,t} + \beta_{3,\tau}CSAD_{t-1} + \varepsilon_t$									
$\beta_{2,25\%}$	0.5592 (0.9125)	2.0053 (0.4572)	−0.2756 (−1.2707)	0.7371 (0.1681)	−2.7429 (0.9750)	−0.7206 (−0.4594)	−0.1338 (−0.0835)	−0.1594 (−0.2152)	1.3169 (1.1034)
$\beta_{2,50\%}$	0.3781 (1.068)	1.5065 (0.2770)	−0.6358 (–0.2447)	0.2341 (0.1658)	−1.1859 (−0.2473)	1.8755 (2.7586)***	1.1785 (1.0842)	0.8218 (0.4888)	2.5548 (2.0818)***
$\beta_{2,75\%}$	0.9774 (0.9422)	0.9838 (0.1926)	3.1622 (2.8676)	−0.0230 (-0.0067)	−0.8730 (−0.1311)	0.6302 (0.1931)	4.4948 (2.3278)***	0.1772 (0.0673)	3.2173 (1.8017)**
Model 2: $CSAD_{t,\tau} = \alpha + \beta_{1,\tau}D_u\left|R_{m,t}\right| + \beta_{2,\tau}D_uR^2_{m,t} + \beta_{3,\tau}CSAD_{t-1} + \varepsilon_t$									
$\beta_{2,25\%}$	1.8245 (3.5844)***	1.8701 (0.1500)	6.1438 (2.0964)***	0.3377 (0.0535)	2.1947 (0.2580)	5.2872 (0.5071)	−0.1338 (−0.0835)	3.8791 (1.2650)	5.9059 (4.8965)***
$\beta_{2,50\%}$	2.7183 (2.8480)***	1.5129 (0.1209)	8.7830 (5.3716)***	0.2804 (0.0465)	9.8039 (1.2883)*	6.4375 (1.3382)*	1.1785 (1.0842)	6.8309 (3.3951)***	7.8780 (5.5068)***
$\beta_{2,75\%}$	4.8193 (2.4514)***	1.0661 (0.1445)	14.4704 (1.2785)	0.0235 (0.1433)	16.6296 (5.4609)***	14.1913 (0.6128)	4.4948 (2.3278)***	12.0686 (2.7792)***	8.4628 (2.6839)***
Model 3: $CSAD_{t,\tau} = \alpha + \beta_{1,\tau}D_d\left|R_{m,t}\right| + \beta_{2,\tau}D_dR^2_{m,t} + \beta_{3,\tau}CSAD_{t-1} + \varepsilon_t$									
$\beta_{2,25\%}$	1.3094 (3.8465)***	4.9718 (4.9120)***	0.1992 (2.0994)***	0.1375 (0.1268)	−0.3607 (−0.1115)	2.5753 (1.058)	0.6497 (0.4493)	1.8314 (1.1627)	2.1378 (1.2833)*
$\beta_{2,50\%}$	1.2783 (2.1163)***	4.9597 (3.0631)***	0.1925 (3.1076)***	2.6818 (0.9606)	−0.6794 (−0.1630)	5.2475 (2.9724)***	1.5035 (1.9655)***	4.0208 (2.2623)***	3.9709 (1.7219)**
$\beta_{2,75\%}$	2.7744 (14.1042)***	11.1060 (2.5170)***	0.1027 (0.5466)	2.3951 (2.0856)***	0.6678 (0.1481)	8.7184 (2.1040)***	1.7501 (0.6264)	5.8626 (1.5050)*	8.1222 (3.0248)***
Model 4: $CSAD_{t,\tau} = \alpha + \beta_{1,\tau}\left|R_{m,t}\right| + \beta_{2,\tau}R^2_{m,t} + \beta_{3,\tau}D_{u,oil}R^2_{m,t} + \beta_{4,\tau}D_{u,vol}R^2_{m,t} + \beta_{5,\tau}CSAD_{t-1} + \varepsilon_t$									
$\beta_{2,25\%}$	1.3054 (0.0417)**	2.2197 (1.1142)	2.4596 (1.5267)***	−1.6466 (-0.3534)	−2.6813 (−2.1327)***	3.3210 (3.9193)***	1.4800 (1.1149)*	0.2736 (0.1817)	2.9571 (2.0903)***
$\beta_{2,50\%}$	0.3709 (0.9643)	2.6171 (1.2979)***	3.9154 (2.8467)***	−0.4795 (−0.2221)	−1.3452 (−0.2601)	2.0480 (0.4802)	0.6770 (0.2230)	−0.0554 (−0.0371)	3.5622 (3.0225)***
$\beta_{2,75\%}$	−0.8779 (−1.0136)	1.2558 (0.1312)	2.9782 (0.4205)	−1.0679 (−0.2680)	−0.3401 (−0.0762)	−0.1961 (−0.0399)	4.9845 (1.9112)***	−1.2219 (−0.4642)	5.1120 (1.9759)***
$\beta_{3,25\%}$	0.5162 (0.6825)	0.1426 (0.0322)	0.1481 (0.1220)	2.2400 (0.9749)	1.6193 (5.119)***	−3.1934 (−17375)**	2.7596 (1.1817)	0.9380 (0.9040)	−1.4117 (−1.1385)

(Table 4 Continued)

(Table 4 Continued)

$\beta_{3,50\%}$	0.9560 (2.7587)***	−0.5798 (−0.2093)	1.0723 (2.4949)***	0.6710 (1.1636)	−1.6559 (−0.4996)	−2.8169 (−0.8290)	3.8086 (0.9352)	1.0533 (0.9182)	−1.0684 (−1.5642)*
$\beta_{3,75\%}$	1.7226 (2.6839)***	0.7839 (0.3036)	0.5930 (0.1052)	0.9303 (0.2062)	−0.4636 (−0.1492)	−2.8916 (−0.5595)	1.9901 (0.4220)	2.5618 (1.4346)*	−1.9214 (−1.0852)
$\beta_{4,25\%}$	−1.0242 (−1.7323)**	−0.3712 (−0.1064)	−2.4750 (−1.8563)**	1.4461 (0.7211)	4.8792 (2.5627)***	−0.4029 −0.25000	−1.1777 (−1.2720)	−0.2506 (−0.2152)	−0.1919 (−0.1635)
$\beta_{4,50\%}$	−0.2523 (−0.7574)	−0.4265 (−0.0849)	−3.8833 (−4.0963)***	0.4427 (0.3903)	5.4474 (2.2847)***	−1.3319 (−0.3551)	0.8581 (0.3063)	−0.1101 (−0.0820)	0.9143 (1.2975)
$\beta_{4,75\%}$	0.5303 (0.8178)	−1.0163 (-0.2815)	−1.5314 (-0.3876)	0.4904 (0.4015)	5.5944 (1.4687)*	−2.1923 (-0.5530)	−1.5122 (-0.8909)	1.4102 (0.9040)	−1.0749 (−0.6004)
Model 5: $CSAD_{t,\tau} = \alpha + \beta_{1,\tau}\left|R_{m,t}\right| + \beta_{2,\tau}R^2_{m,t} + \beta_{3,\tau}D_{d,oil}R^2_{m,t} + \beta_{4,\tau}D_{d,vol}R^2_{m,t} + \beta_{5,\tau}CSAD_{t-1} + \varepsilon_t$									
$\beta_{2,25\%}$	0.8171 (0.6937)	1.9910 (0.2733)	0.1328 (0.0902)	2.03955 (0.4166)	3.8172 (1.5518)**	−0.2753 (−0.1947)	3.2037 (1.8345)***	0.9609 (0.5668)	1.3344 (0.9662)
$\beta_{2,50\%}$	1.0746 (2.9341)***	1.6107 (0.2056)	1.1044 (1.9621)**	0.6002 (0.4864)	2.4462 (0.8557)	−2.1008 (−1.0107)	5.5216 (1.0669)	0.8877 (0.4936)	3.4081 (3.3762)***
$\beta_{2,75\%}$	1.3750 (1.5715)***	1.0234 (0.0799)	2.0398 (0.4068)	0.3528 (0.0458)	4.7906 (0.8186)	−5.2801 (−0.7338)	6.8604 (1.3957)*	2.7501 (1.1510)	2.1157 (0.7897)
$\beta_{3,25\%}$	−0.5350 (−0.7074)	−0.1426 (−0.03222)	−0.1481 (−0.1220)	−2.2400 (−0.9744)	−1.6193 (−5.1191)***	3.1934 (1.7374)**	−2.8613 (−1.8983)***	−0.9380 (−0.9040)	1.4541(1.1463)
$\beta_{3,50\%}$	−0.9560 (−2.7588)***	0.5798 (0.2093)	−1.0723 (−2.4949)***	−0.6434 (−1.2514)	1.6559 (0.4996)	2.8169 (1.7635)**	−3.9251 (−0.8810)	−1.0533 (−0.9182)	1.0684 (1.5646)*
$\beta_{3,75\%}$	−1.7226 (−2.6660)***	−0.7839 (−0.3037)	−0.5930 (−0.1052)	−0.9303 (−0.2062)	0.4636 (0.1492)	2.8916 (0.5595)	−3.2501 (−0.8532)	−2.5618 (−1.4346)*	1.9214 (1.0856)
$\beta_{4,25\%}$	1.0061 (1.7016)***	0.3712 (0.1064)	2.4750 (1.8563)**	−1.4461 (−0.7220)	−4.8792 (−2.5627)***	0.4029 (0.2500)	0.0238 (0.8027)	0.2506 (0.2052)	0.2211 (0.1819)
$\beta_{4,50\%}$	0.2523 (0.7574)	0.4265 (0.0849)	3.88339 (4.0963)***	−0.4175 (−0.3380)	−5.4474 (−2.2847)***	1.3319 (5.1493)***	0.01045 (0.2526)	0.1101 (0.0820)	−0.9143 (−1.2974)*
$\beta_{4,75\%}$	−0.5303 (−0.8099)	1.0163 (0.2815)	1.5314 (0.3876)	−0.4904 (−0.4015)	−5.5944 (−1.4687)***	2.1923 (0.5530)	0.0180 (0.3929)	−1.4102 (−0.9040)	1.0749 (0.6005)

Notes: *t*-ratios are in parentheses. *10% level of significance; **5% level of significance; ***1% level of significance. The estimation is at 25%, 50% and 75% quantiles. We only present the herding behaviours parameters, which is β_2 for model 1, 2, and 3; β_2, β_3, and β_4 for model 4 and 5 with each quantile. The 'robust' standard errors use the heteroscedasticity-robust variant from Koenker and Zhao (1994).

based on ESG criteria, which indicates that the companies are meeting the environmental and social criteria and must have strong governance norms. The question is whether the investors of the ESG indices herd as in other assets investors as we acknowledge that herding behaviour in the financial market leads to a financial crisis. Using ESG indices of an emerging market, our study shows no evidence of herding behaviour, even during upwards and downwards market episodes. However, the result is mixed when we include global factors—oil and implied volatility. Most samples do not show herding; only a few, such as the Egypt and India market, exhibit the behaviour during upwards implied volatility and oil price, respectively; Brazil, China and Taiwan market herd during downwards oil price episodes. Using quantile regression confirms the results, wherein the herd is prevailing to those indices only at a specific area (quantile) of return distribution. Overall, the herding behaviour does not exist in emerging markets' ESG indices. It is due to the large size of companies with strong governance norm included in the indices, and the information on the companies are widely available. The investors do not rely on others in the investment decision. Moreover, it is important to take into account that the behaviour of ESG indexes and investor engagement may change over time as ESG awareness and regulatory frameworks continue to advance in emerging nations.

The herding behaviour indicates the level of market efficiency; therefore, policymakers could trace the market efficiency through herding behaviour (markets are less efficient if herding exists). Policymakers should be able to adopt suitable policies to lead the market towards more efficient points by monitoring and enhancing the quality of information transmission. Furthermore, developing and implementing ESG standards in the financial markets is also greatly aided by emerging market governments' crucial regulatory roles. The regulator maintains markets' fairness by approving operating standards and granting licenses to exchanges and clearing houses.

The findings are helpful for investors to identify which market conditions are associated with the rational and irrational behaviour of investors. Herding behaviour findings are vitally important to the market participants, such as institutional investors and individual investors, because it sheds light on the behaviour of market participants and indicates how the investors behave when making decisions on buying or selling financial securities. Investors could also benefit from the results of their choice of optimal portfolio to enhance the return on their investment.

These studies are limited by not including Hwang and Salmon and weighted cross-sectional variances models due to the limitation of the data and different scopes of variables. Future studies could incorporate the models and look into different variables in investigating herding behaviour.

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