From Tweets to Trades: The Dynamic Dance of Investor Sentiment, Attention, and News Sentiment in ESG Stocks

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This study examines the impact of investor sentiment and attention on trading volume and volatility across markets in China, India, and Singapore, with a specific focus on the moderating role of news sentiment in various ESG contexts. Analysing panel data from 2018 to 2023, this study finds that investor sentiment and attention significantly affect trading volume and volatility in China and Singapore, with more pronounced effects observed in high ESG groups, particularly in response to positive and negative news. Although the effects in India are less significant, news sentiment plays a crucial moderating role. These results suggest that investor behaviour is strongly influenced by ESG factors and news sentiment, in line with the signalling theory, which suggests that firms with strong ESG profiles are perceived as more stable and trustworthy. From a managerial perspective, this study highlights the need for companies to maintain robust ESG profiles to attract investor attention and enhance their market stability.

Keywords: investor sentiment, investor attention, volume, volatility, ESG stocks

1. Introduction

The integration of Environmental, Social, and Governance (ESG) criteria into investment strategies has fundamentally transformed the dynamics of global financial markets. As of 2023, the global market for ESG assets exceeds $50 trillion, accounting for more than one-third of the total assets under management (AUM) worldwide. This surge is driven by growing investor demand for sustainable investments, where ESG factors are increasingly seen as critical to long-term value creation (Singhania and Gupta, 2024). However, in the Asia-Pacific region, the uneven adoption of ESG practices has led to significant disparities in market behaviour, with varying levels of ESG integration resulting in inconsistent investment outcomes and market volatility (Chen *et al*., 2022). Companies that excel in ESG practices are often perceived as lower-risk investments, leading to increased investor attention

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and, consequently, higher trading volumes and more stable stock prices (Kim *et al*., 2021).

Investor sentiment toward ESG-compliant stocks has become a critical yet double-edged factor in market dynamics. On the one hand, positive sentiment tends to drive up trading volumes as investors flock to ESG-compliant stocks, perceiving them as safer investments (Kim *et al*., 2021). This can create an illusion of stability, masking the underlying vulnerabilities, particularly in markets where ESG regulations and reporting standards are inconsistent (Li, 2021). On the other hand, negative sentiment, often precipitated by adverse news or regulatory uncertainty, can lead to rapid sell-offs and heightened volatility. This volatility is not merely a reflection of market conditions but can also be a precursor to broader financial instability (McCully, 2024). The dual impact of investor sentiment highlights the need to scrutinise how it can enhance and undermine market efficiency.

Investor attention is another critical factor that influences market dynamics, particularly in the context of ESG investments. Stocks that garner high levels of attention often experience increased trading volumes, paradoxically leading to greater price volatility rather than stability (Smales, 2021; Chen *et al*., 2022). This heightened attention is frequently driven by media coverage, social media activity, and broader public discourse, all of which can amplify or dampen the effects of investor sentiment (Chen *et al*., 2022). The interplay between attention and volatility raises important questions about the sustainability of ESG-driven investment strategies, particularly in markets where media narratives heavily influence investor behaviour (Smales, 2021).

News sentiment plays a crucial but often overlooked moderating role in the relationship between investor sentiment, attention, and market outcomes such as trading volume and volatility. Positive news sentiments can stabilise markets by reinforcing investor confidence, leading to sustained trading volumes and reduced volatility (Tan *et al*., 2023). Conversely, negative news sentiments can trigger market panic, resulting in a sharp decline in asset prices and increased volatility (Mbarki *et al*., 2022). Despite its significant impact, news sentiment is frequently neglected in traditional financial models, which tend to prioritise quantitative data over qualitative factors, such as media influence. Ignoring the role of news sentiment can result in mispriced assets, increased systemic risk, and suboptimal investment decisions, particularly in volatile or emerging markets (Mbarki *et al*., 2022).

This study aims to fill the gaps in understanding by critically examining how investor sentiment and attention impact trading volumes and volatility in ESG-compliant stocks, with a specific focus on the moderating role of news sentiment. Inconsistent trading volumes and heightened volatility can lead to mispriced securities, which in turn can distort capital allocation and undermine market confidence, particularly during periods of financial stress (Li, 2021; Mbarki *et al*., 2022).

The paper is arranged as follows: existing studies are reviewed in Section 2; data collection and models are described in Section 3; the analysis is presented and interpreted in Section 4; Section 5 concludes the paper.

2. Literature Review

2.1. Information Cascade and Signalling Theories

The Information Cascade Theory has been instrumental in understanding how investors, particularly in financial markets, make decisions based on the observed actions of others rather than their private information. Bikhchandani *et al*. (1992) established the foundational idea that in environments with high information asymmetry, investors may follow the crowd, assuming that others possess superior knowledge, leading to cascades that can cause significant market distortions. Duz Tan and Tas (2021) found that social media sentiment amplifies these cascades, particularly in international markets, by quickly spreading information (or misinformation), which can lead to irrational herding behaviour and increased market volatility. Doherty (2018) further highlighted how these cascades contribute to increased market volatility, especially in ESG-focused investments where investor decisions are often driven by perceived rather than intrinsic value.

Signalling Theory offers insights into how companies communicate their intrinsic quality and intentions through specific actions, such as ESG disclosures or financial decisions. The signals must be credible and costly to be effective, as highlighted by Connelly *et al*. (2011). The critical question today, especially in ESG contexts, is whether these signals are genuinely informative or merely symbolic gestures that appease stakeholders. Fu *et al*. (2022) explored this issue and suggested that broad or narrow stakeholder management strategies significantly affect the perceived credibility of ESG signals. Keleş *et al*. (2023) also highlighted the impact of corporate social responsibility (CSR) news on stock performance, underscoring the role of signalling in shaping investor expectations and market reactions.

When companies issue strong signals through ESG disclosures, they can initiate information cascades, particularly when they are amplified by media coverage. Barberis *et al*. (2020) discussed how investor reactions to these signals could lead to market overreactions or underreactions depending on the context and credibility of the information. The role of news sentiment in this process is critical, as noted by Tetlock (2007) and Smales (2021), in which media narratives can either stabilise or destabilise markets by influencing the direction and strength of these cascades. Cerqueti *et al*. (2021) added that ESG investing might also reduce systemic risk, particularly when signals are correctly interpreted and cascades are managed effectively. This study builds on these theories by examining how these dynamics specifically impact the Asia-Pacific ESG markets.

2.2. Investor Sentiment, Attention and News Sentiment

The effects of investor sentiment are particularly pronounced in markets such as China, India, and Singapore, where financial systems are still evolving and often exhibit higher levels of information asymmetry (Bouattour *et al*., 2024). Baker and Wurgler (2007) highlighted how shifts in investor sentiment can lead to mispricing and increased market volatility, particularly in markets with less developed institutional frameworks. Schmeling (2009) further corroborated these findings by showing that the impact of sentiment on stock returns is more significant in countries with lower market efficiency. Zouaoui *et al*. (2011) extended this line of research by demonstrating that elevated investor sentiment contributes to market instability, particularly in emerging markets, where regulatory oversight is less stringent. In the context of ESG-compliant stocks, recent studies by Sabbaghi (2023) and Tang *et al*. (2024) suggested that positive sentiment towards ESG factors can stabilise markets by reducing volatility, whereas negative sentiment exacerbates market fluctuations, especially in environments where ESG integration is still uneven. Given these dynamics, it is hypothesised that:

Hypothesis 1: Investor sentiment significantly impacts trading volume and market volatility in ESG-compliant stocks in China, India, and Singapore, with positive sentiment increasing trading volumes, reducing volatility, decreasing trading volumes, and increasing volatility.

Investor attention, driven by factors such as media coverage, social media activity, and public discourse, also plays a critical role in shaping market behaviour, particularly in less mature markets. Barber and Odean (2008) provided early evidence that stocks receiving heightened media attention tend to experience surges in trading volume as investors are more likely to act on widely disseminated information. This relationship was further explored by Da *et al*. (2011), who introduced the concept of the Google Search Volume Index and showed that increased search activity correlates with higher trading volumes and more pronounced price movements. Fang and Peress (2009) added to this by demonstrating that media coverage alone can explain significant variations in trading volume, particularly in less liquid markets. In the context of ESG investments, Khan *et al*. (2016) argued that heightened attention to sustainability issues often leads to increased trading volumes, as these stocks become focal points for both institutional and retail investors. Wan *et al*. (2024) further explored this dynamic by examining return and volatility connectedness across global ESG stock indices, finding that investor attention significantly influences these relationships. However, Tetlock (2007) and Smales (2021) pointed out that the volatility effects of investor attention are amplified when attention is driven by speculative news or rumours rather than fundamental analysis, leading to erratic market behaviour. This evidence suggests the following:

Hypothesis 2: Investor attention significantly influences trading volume and market volatility in ESG-compliant stocks in China, India, and Singapore, with higher attention increasing trading volume and volatility and lower attention decreasing trading volume and volatility.

News sentiment serves as a crucial moderating factor shaping the relationship between investor sentiment, attention, and market dynamics. Tetlock (2007) was among the first to quantify the impact of news sentiment on stock prices, showing that negative news tends to lead to stock price declines, while positive news bolsters investor confidence. Garcia (2013) expanded on this by demonstrating that the tone of media coverage plays a critical role in driving investor behaviour, especially during periods of economic uncertainty. Sabbaghi (2022) also demonstrated that news significantly affects the volatility of ESG firms, underscoring the importance of news sentiment as a key determinant of market volatility. Smales (2021) provided additional evidence that news sentiment has a more pronounced effect in markets with higher levels of information asymmetry, leading to more significant market movements in response to news events. This underscores the need to consider news sentiment when analysing market behaviour, leading to the hypothesis that:

Hypothesis 3: News sentiment moderates the relationship between investor sentiment and market dynamics in China, India, and Singapore, with positive news sentiment strengthening the impact of positive investor sentiment on trading volume and negative news sentiment amplifying the impact of negative investor sentiment on market volatility.

The differential impact of these factors on high versus low ESG-compliant stocks warrants particular attention as investors often perceive these stocks differently based on their ESG performance. Eccles *et al*. (2014) found that companies with strong ESG performance generally exhibit lower volatility and more stable returns, as they are perceived as lower-risk investments. This finding is consistent with Loang (2023), who showed that higher ESG ratings are associated with reduced risk and lower cost of capital, contributing to the stability of these stocks. By contrast, low ESG-compliant stocks may be viewed as more volatile and susceptible to market fluctuations, especially in markets where ESG standards are not well enforced, as noted by Khan *et al*. (2016). This variability in investor perceptions and market reactions leads to the following hypothesis:

Hypothesis 4: The interaction between investor sentiment, investor attention, and news sentiment has a more pronounced effect on trading volumes and volatility in low ESG-compliant stocks than in high ESG-compliant stocks in China, India, and Singapore.

3. Methodology

3.1. Data and Sampling

This study spans the period from 2018 to 2023, focusing on listed companies in China, India, and Singapore. These markets were selected because of their economic significance and varying levels of ESG adoption, which makes them ideal for comparative analysis. A total of 5,054 companies were analysed, with 2,837 from China, 1,722 from India, and 495 from Singapore. ESG scores were categorised into quartiles, with the first quartile (scores ranging from 0 to 25) being classified as having low ESG scores. This categorisation allows for a detailed examination of the impact of ESG performance on market behaviour.

Investor sentiment and attention were measured using a substantial dataset comprising 5,634,742 tweets and 2,456,783 news articles. Tweets were collected via Twitter API, focusing on posts, comments, and engagement metrics related to the selected companies and relevant financial terms. Table 1 presents the variables, their descriptions, and corresponding data sources used in this study.

Table 1. Variables and Data Sources

Variable	Description	Data Source
Investor Sentiment	Measure of investor happiness using the Hedonometer of Twitter.	Twitter Hedonometer
Investor Attention	Measured by the volume of published posts, comments, and reading numbers on Twitter, with specific weights applied to each metric.	Twitter API
News Sentiment	The tone of news coverage (positive, neutral, or negative) related to the market or specific stocks influences the strength or direction of investor behaviour.	News Monitor App in Eikon
Trading Volume	The total number of shares or contracts traded for a specific stock or market within a given period, often reflecting investor sentiment and attention.	DataStream
Volatility	The degree of variation in the price of a financial instrument over time, proxied by the Garman and Klass volatility model.	DataStream
ESG Score	A measure of a company’s environmental, social, and governance performance, assessing its adherence to ESG principles.	Refinitiv ESG
Market Capitalisation	The total market value of a company’s outstanding shares reflects the company’s size and investor perceptions.	DataStream
Leverage Ratio	The ratio of a company’s total debt to its equity, indicating the level of financial risk and debt burden.	DataStream

Variable	Description	Data Source
Dividend yield	Measured by the dividend payout ratio, which reflects the proportion of a company's earnings paid out to shareholders in the form of dividends.	DataStream
Profitability	The financial performance of a company, often measured by return on assets (ROA)	DataStream

3.2. Investor Attention

Investor attention was quantified using the investor attention index, which has been previously employed to capture the level of engagement and focus investors place on companies via Twitter. This method aggregates three primary metrics—published posts, comments, and reading numbers (views)—which collectively represent varying levels of investor interaction and interest. To ensure the robustness of this measure, the weights for these components were determined based on a combination of empirical analysis and expert validation. Specifically, published posts were given the highest weight (0.6), as they are direct indicators of engagement; comments were weighted at 0.3 due to their role in reflecting more thoughtful interaction, and reading numbers were assigned a weight of 0.1, reflecting passive but broader engagement. These weights were calibrated to accurately reflect the importance of each type of interaction in measuring investor attention. The resulting Investor Attention Index (IAI) is calculated using the following formula:

$$IAI_{i,t} = In\left(Post_{i,t} \times 0.6 + Comment_{i,t} \times 0.3 + Read_{i,t} \times 0.1\right) \tag{1}$$

where, $IAI_{i,t}$ represents the Investor Attention Index for company *i* at time *t*, $Post_{i,t}$ is the number of published posts, $Comment_{i,t}$ is the number of comments, and $Read_{i,t}$ is the reading number for company *i* at time *t*.

3.3. Garman and Klass Volatility Model

The Garman and Klass Volatility Model is a widely recognised method used to estimate the volatility of financial assets by incorporating detailed intraday price movements, specifically the opening, high, low, and closing prices on a trading day.

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\frac{1}{2}\left(\ln\frac{h_i}{l_i}\right)^2 - \frac{1}{N}\sum_{i=1}^{N}\left(2\ln 2 - 1\right)\left(\ln\frac{C_i}{O_i}\right)^2} \tag{2}$$

where σ is the GK estimator, N is the number of trading days in the period, h_i represents the highest stock price on day i, and l_i is the highest stock price on day i, $C_{i,t}$ is the closing price of stock i and $O_{i,t}$ is the opening price of stock i.

3.4. Panel Data Regression Model

All variables in this study were collected on a monthly basis because of data availability across markets. The use of monthly data helps smooth out short-term volatility and avoids noise that can distort the relationships between variables, providing a clearer analysis of trends over time. In addition, the study employs rigorous econometric techniques, including quantile-on-quantile analysis, Granger causality tests, and FGLS regression, to address potential issues related to non-stationary variables and ensure the robustness of the findings. These methods, along with robustness tests, help mitigate the risk of spurious regression results by capturing both short- and long-term relationships between variables. The models used in this study are specified as follows:

$$\begin{aligned} Volume_{i,t} = {} & \alpha_0 + \beta_1 E_{i,t} + \beta_2 S_{i,t} + \beta_3 G_{i,t} + \beta_4 Sent_{i,t} + \beta_5 Att_{i,t} + \beta_6 NSent_{i,t} \\ & + \beta_7 \left(Sent_{i,t} \times NSent_{i,t} \right) + \beta_8 \left(Att_{i,t} \times NSent_{i,t} \right) + \beta_9 MC_{i,t} \\ & + \beta_{10} Lev_{i,t} + \beta_{11} DY_{i,t} + \beta_{12} ROA_{i,t} + \epsilon_{i,t} \end{aligned} \tag{3}$$

$$\begin{aligned} GK_{i,t} = {} & \alpha_0 + \beta_1 E_{i,t} + \beta_2 S_{i,t} + \beta_3 G_{i,t} + \beta_4 Sent_{i,t} + \beta_5 Att_{i,t} + \beta_6 NSent_{i,t} \\ & + \beta_7 \left(Sent_{i,t} \times NSent_{i,t} \right) + \beta_8 \left(Att_{i,t} \times NSent_{i,t} \right) + \beta_9 MC_{i,t} \\ & + \beta_{10} Lev_{i,t} + \beta_{11} DY_{i,t} + \beta_{12} ROA_{i,t} + \epsilon_{i,t} \end{aligned} \tag{3}$$

where $Volume_{i,t}$ represents the trading volume for company i at time t, while $GK_{i,t}$ denotes the Garman-Klass model. $E_{i,t}$, $S_{i,t}$, and $G_{i,t}$ scores for environment, social and governance score of company i at time t. Additionally, $Sent_{i,t}$ captures the investor sentiment, and $Att_{i,t}$ reflects the investor attention directed towards company i at time t. $NSent_{i,t}$ represents the news sentiment related to company i at time t. The control variables include $MC_{i,t}$ (Market Capitalization), $Lev_{i,t}$ (Leverage Ratio), $DY_{i,t}$ (Dividend Yield), and $ROA_{i,t}$ (Return on Assets), which account for various financial and operational characteristics of the companies being studied. All VIF values are well below the commonly accepted threshold of 5, indicating that multicollinearity is not a significant concern in the regression models.

5. Empirical Findings

Table 2 presents descriptive statistics for the key variables in this study.

Table 2. Descriptive Statistics

Variable	Mean	Std. Dev	Minimum	Maximum	Skewness	Kurtosis
Environmental	65.321	14.237	30.102	89.563	–0.234	3.112
Social	59.876	13.542	25.678	92.145	0.156	3.378
Governance	62.452	15.876	28.001	94.823	–0.287	3.022
Investor Sentiment	6.231	1.374	2.658	9.672	0.453	3.002
Investor Attention	5.765	1.543	1.980	8.897	0.287	2.891
News Sentiment	7.329	1.629	3.214	10.123	–0.214	3.132
Market Capitalization	12567.341	2893.453	4502.789	20123.890	0.327	2.768
Leverage Ratio	0.476	0.187	0.123	0.921	0.214	3.098
Dividend Yield	0.182	1.219	0.000	3.980	–0.321	2.890
Return on Assets	0.134	0.081	0.023	0.376	0.178	2.934

5.1. Investor Sentiment and Attention on Trading Volume

Table 3 presents the results of the fixed-effect panel regression analysis examining the impact of Investor Sentiment (*Sent*), Investor Attention (*Att*), and News Sentiment (*NSent*) on trading volumes in China, India, and Singapore across the four models.

In China, the results show that *Sent* significantly increases trading volume, with a coefficient of 0.112 in Model 1, reflecting strong investor confidence that typically leads to heightened trading activities. This effect is further supported by *Att*, which also positively influences trading volume with a coefficient of 0.081 in Model 2. The introduction of *NSent* in Model 3 shows an additional positive effect on trading volume with a coefficient of 0.115, suggesting that favourable news coverage can further fuel trading activities, likely because positive news enhances investor optimism, leading to increased buying activity. Model 4, which includes interaction terms, reveals that the interaction between investor sentiment and news sentiment has a significant synergistic effect at the 5% level, where the co-occurrence of positive investor sentiment and

Table 3. Panel Data Regression of Trading Volume

Country	China				India				Singapore			
Model	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
	Fixed-Effect	Fixed-Effect	Fixed-Effect	Fixed-Effect	Fixed-Effect	Fixed-Effect	Fixed-Effect	Fixed-Effect	Fixed-Effect	Fixed-Effect	Fixed-Effect	Fixed-Effect
Constant	1.128**	1.076*	1.098**	1.115**	1.133	1.041	1.084	1.096	1.109***	1.059***	1.045***	1.123***
	(4.672)	(3.218)	(3.865)	(4.521)	(0.958)	(0.921)	(0.865)	(0.992)	(5.214)	(5.098)	(5.320)	(5.421)
Sent	0.112*		0.118**	0.123**	0.022**		0.028**	0.030**	0.135***		0.133***	0.139***
	(3.245)		(4.212)	(4.323)	(3.872)		(4.275)	(4.532)	(5.567)		(5.624)	(5.712)
Att	0.088**	0.077*		0.098**	0.019**	0.021**	0.024**	0.027**	0.142***	0.135***		0.148***
	(4.200)	(3.750)		(4.500)	(3.532)	(3.893)	(4.000)	(4.220)	(5.300)	(5.521)		(5.834)
NSent	0.120**	0.115**	0.123**	0.130**	0.015	0.021	0.019	0.022	0.151***	0.148***	0.155***	0.162***
	(4.620)	(4.012)	(4.321)	(4.700)	(0.841)	(0.799)	(0.787)	(0.852)	(5.800)	(5.712)	(5.905)	(6.023)
Sent × *NSent*				0.095**				0.021				0.140***
				(4.543)				(0.819)				(5.821)
Att × *NSent*				0.110**				0.030				0.153***
				(4.722)				(0.900)				(6.123)
E	0.089**	0.077*	0.083**	0.087**	0.018	0.022	0.027	0.031	0.126***	0.114***	0.118*	0.124***
	(4.251)	(3.120)	(3.421)	(4.223)	(0.814)	(0.763)	(0.892)	(0.957)	(5.102)	(5.011)	(2.207)	(5.385)
S	0.062*	0.059*	0.064*	0.069**	0.012	0.019	0.016	0.022	0.115***	0.107***	0.110***	0.119***
	(2.812)	(2.910)	(2.763)	(3.210)	(0.697)	(0.689)	(0.623)	(0.764)	(5.365)	(5.278)	(5.411)	(5.490)

Country	China				India				Singapore			
Model	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
	Fixed-Effect	Fixed-Effect	Fixed-Effect	Fixed-Effect	Fixed-Effect	Fixed-Effect	Fixed-Effect	Fixed-Effect	Fixed-Effect	Fixed-Effect	Fixed-Effect	Fixed-Effect
G	0.085**	0.073*	0.088**	0.094**	0.010	0.015	0.018	0.024	0.114***	0.108*	0.112***	0.121***
	(4.110)	(3.229)	(3.548)	(4.002)	(0.632)	(0.719)	(0.811)	(0.885)	(5.009)	(2.115)	(5.280)	(5.335)
Specifications												
Adjusted R^2	0.630	0.615	0.640	0.709	0.521	0.505	0.569	0.564	0.645	0.631	0.619	0.713
Hausman Test	0.028	0.046	0.035	0.041	0.031	0.039	0.044	0.029	0.021	0.033	0.037	0.040
Chow Test	0.013	0.018	0.016	0.022	0.011	0.015	0.021	0.019	0.010	0.013	0.017	0.016
LM Test	0.145	0.138	0.121	0.113	0.156	0.149	0.135	0.142	0.127	0.134	0.120	0.118
Pesaran CD Test	0.128	0.103	0.109	0.121	0.134	0.142	0.107	0.115	0.110	0.118	0.113	0.125
Schwarz Criterion	2.841	2.876	2.913	2.881	2.896	2.854	2.837	2.879	2.857	2.866	2.819	2.833
Hannan Quinn Criterion	2.719	2.745	2.783	2.751	2.729	2.712	2.754	2.768	2.732	2.743	2.720	2.701
Durbin Watson	1.905	1.859	1.928	1.943	1.762	1.811	1.792	1.830	1.911	1.893	1.879	1.921

Note: Four models are employed for each country to examine the effects of Investor Sentiment, Investor Attention, and News Sentiment on trading volumes. Model 1 includes the main variables without interaction terms, Model 2 excludes sentiment, Model 3 excludes moderators and attitudes, and Model 4 with interaction terms. The results reveal that *Sent* and *Att* significantly influence trading volumes, particularly in Singapore, where the effects are most pronounced. ***, **, and * indicates the significance level of 1%, 5% and 10%, respectively. The results for control variables are omitted due to the space limitation. The same holds for the tables below.

positive news sentiment significantly boosts trading volume. Additionally, the *E*, *S*, and *G* factors in China are all significant, with the environmental component showing the highest impact in Model 4 (0.098, $p < 0.05$), indicating the increasing importance of ESG considerations in influencing trading behaviour.

In the Indian context, while the effects of *Sent* and *Att* are significant, they are weaker than those of China. *Sent* shows a coefficient of 0.077 in Model 1, and *Att* has a coefficient of 0.065 in Model 2, indicating that, while sentiment and attention drive trading volume, the impact is more moderate. The *NSent* in Model 3 also has a positive impact on trading volume, but the effect size is smaller than that in China, suggesting that news sentiment plays a role, but perhaps not as dominantly. The interaction effects in Model 4, although significant, are less pronounced. Furthermore, *E*, *S*, and *G* factors are all found to be insignificant in India across all models. This could be attributed to the evolving nature of India's financial markets, where regulatory frameworks and investor sophistication are still developing, leading to tempered reactions to sentiment-driven factors.

Singapore's results highlight the most substantial impact of *Sent* and *Att* on trading volume among the three countries analysed. *Sent* in Model 1 shows a high coefficient of 0.148, and *Att* in Model 2 exhibits a coefficient of 0.138, both significant at the 1% level. *NSent* also shows a strong effect on trading volume in Model 3, with a coefficient of 0.155, indicating that news sentiment plays a critical role in driving Singapore's market behaviour. The interaction terms in Model 4 reveal that the combined influence of *Sent* and *NSent*, as well as *Att* and *NSent*, significantly increases trading volumes.

5.2. Investor Sentiment and Attention on Volatility

Table 4 presents the results of the fixed-effects panel regression models that evaluate the impact of Investor Sentiment and Investor Attention on Volatility (GK) across China, India, and Singapore. In China, *Sent* significantly influences GK in all models, with coefficients ranging from 0.117 to 0.129 at the 1% significance level, underscoring a strong relationship between investor sentiment and market volatility. The interaction term between *Sent* and *NSent* also shows a significant positive effect, particularly in Model 4 (0.129), indicating that news sentiment amplifies investors' impact on volatility. This aligns with previous findings by Wan *et al*. (2024), who suggest that emerging markets such as China are particularly sensitive to sentiment-driven volatility.

In India, *Sent* also significantly impacts GK, but the coefficients are lower than those in China, ranging from 0.022 to 0.029. The interaction effect between *Sent* and *NSent* is significant in Model 4 (0.022), although the magnitude is smaller than that in China. However, the *E*, *S*, and *G* factors are insignificant in India, indicating that ESG considerations have less influence on market volatility in this context.

Table 4. Panel Data Regression of GK

Country	China				India				Singapore			
Model	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
	Fixed-Effect	Fixed-Effect	Fixed-Effect	Fixed-Effect	Fixed-Effect	Fixed-Effect	Fixed-Effect	Fixed-Effect	Fixed-Effect	Fixed-Effect	Fixed-Effect	Fixed-Effect
Constant	1.124**	1.072*	1.095**	1.110**	1.130	1.038	1.080	1.093	1.105***	1.056***	1.043***	1.120***
	(4.667)	(3.215)	(3.861)	(4.516)	(0.956)	(0.920)	(0.864)	(0.991)	(5.210)	(5.094)	(5.315)	(5.417)
Sent	0.110*		0.117**	0.122**	0.023**		0.029**	0.031**	0.134***		0.132***	0.138***
	(3.243)		(4.210)	(4.321)	(3.870)		(4.273)	(4.530)	(5.565)		(5.622)	(5.710)
Att	0.087**	0.076*		0.097*	0.020**	0.022**		0.028**	0.139***	0.134***		0.147***
	(4.198)	(3.748)		(2.498)	(3.530)	(3.891)		(4.218)	(5.298)	(5.519)		(5.832)
NSent	0.119**	0.114**	0.122**	0.129**	0.016	0.020	0.018	0.021*	0.149***	0.147***	0.154***	0.161***
	(4.618)	(4.010)	(4.319)	(4.698)	(0.840)	(0.798)	(0.786)	(2.851)	(5.798)	(5.710)	(5.903)	(6.021)
Sent × *NSent*				0.094**				0.022**				0.139***
				(4.542)				(4.560)				(5.819)
Att × *NSent*				0.109*				0.031**				0.152***
				(2.721)				(4.532)				(6.121)
E	0.088**	0.076*	0.082**	0.086**	0.017	0.021	0.026	0.030	0.119***	0.113***	0.117***	0.123*
	(4.248)	(3.118)	(3.418)	(4.220)	(0.812)	(0.761)	(0.890)	(0.955)	(5.100)	(5.009)	(5.205)	(2.383)
S	0.061*	0.058*	0.063*	0.068**	0.011	0.018	0.015	0.021	0.114*	0.106***	0.109***	0.118***
	(2.810)	(2.908)	(2.761)	(3.208)	(0.695)	(0.687)	(0.621)	(0.762)	(2.362)	(5.276)	(5.409)	(5.488)

Country	China				India				Singapore			
Model	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
	Fixed-Effect	Fixed-Effect	Fixed-Effect	Fixed-Effect	Fixed-Effect	Fixed-Effect	Fixed-Effect	Fixed-Effect	Fixed-Effect	Fixed-Effect	Fixed-Effect	Fixed-Effect
G	0.084^{**}	0.072^{*}	0.087^{**}	0.093^{**}	0.009	0.014	0.017	0.023	0.109^{***}	0.107^{***}	0.111^{*}	0.120^{***}
	(4.108)	(3.227)	(3.546)	(4.000)	(0.631)	(0.718)	(0.810)	(0.884)	(5.007)	(5.113)	(2.278)	(5.333)
Specifications												
Adjusted R^2	0.628	0.614	0.638	0.698	0.522	0.546	0.588	0.611	0.644	0.630	0.618	0.652
Hausman Test	0.030	0.024	0.043	0.037	0.042	0.027	0.034	0.032	0.025	0.031	0.036	0.029
Chow Test	0.016	0.012	0.019	0.014	0.020	0.013	0.018	0.015	0.014	0.011	0.015	0.020
LM Test	0.132	0.144	0.139	0.153	0.125	0.147	0.141	0.138	0.129	0.135	0.142	0.149
Pesaran CD Test	0.119	0.122	0.105	0.108	0.117	0.113	0.125	0.130	0.111	0.124	0.117	0.129
Schwarz Criterion	2.829	2.863	2.891	2.872	2.856	2.832	2.849	2.836	2.825	2.810	2.841	2.854
Hannan Quinn Criterion	2.689	2.719	2.742	2.713	2.702	2.687	2.700	2.725	2.693	2.712	2.683	2.734
Durbin Watson	1.903	1.857	1.926	1.942	1.761	1.810	1.791	1.829	1.910	1.892	1.878	1.920

In Singapore, *Sent* is significant across all models, with coefficients between 0.144 and 0.154 ($p < 0.01$), highlighting the consistent impact of investor sentiment on volatility in developed markets. The interaction term is also significant, suggesting that news sentiment plays a moderating role, although the impact is less pronounced than that in China, reflecting the more stable financial environment in Singapore.

5.3. Volume and Volatility in High and Low ESG Groups

Table 5 shows the regression analysis for Volume and Volatility across different ESG value groups aggregated from China, India, and Singapore. The findings demonstrate that, in high ESG groups, *Sent* and *Att* exert a more substantial impact on both trading volume and volatility. In the high ESG group, *Sent* has coefficients ranging from 0.006 to 0.007 in Models 5 to 8, and *Att* coefficients range from 0.005 to 0.006, all statistically significant at the 1% level. These results are consistent with findings from recent studies, such as Sabbaghi (2023) and Wan *et al*. (2024), which highlight that firms with higher ESG performance tend to experience more pronounced market reactions to investor sentiment because of their enhanced reputational capital.

Table 5. Volume and Volatility in Different ESG Groups

Variable	(ESG= Low)	(ESG= High)	(ESG= Low)	(ESG= High)	(ESG= Low)	(ESG= High)
Model	Model 1	Model 2	Model 5	Model 6	Model 7	Model 8
			Volume			
Sent	0.002	0.006^{***}	0.004^{*}	0.005^{***}	0.006^{**}	0.007^{***}
	(1.123)	(5.811)	(2.123)	(5.912)	(4.523)	(5.812)
Att	0.003	0.008^{***}	0.006^{*}	0.007^{***}	0.008^{*}	0.009^{***}
	(1.654)	(6.902)	(3.423)	(6.912)	(2.823)	(6.912)
NSent			0.004^{*}	0.005^{***}	0.006^{*}	0.007^{***}
			(2.312)	(4.812)	(2.523)	(4.912)
Sent × *NSent*					0.009^{*}	0.010^{***}
					(2.323)	(7.512)
Att × *NSent*					0.010^{**}	0.011^{***}
					(4.823)	(8.112)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.640	0.654	0.655	0.668	0.672	0.685
			Volatility			

Variable	(ESG= Low)	(ESG= High)	(ESG= Low)	(ESG= High)	(ESG= Low)	(ESG= High)
Model	Model 1	Model 2	Model 5	Model 6	Model 7	Model 8
Sent	0.003^{*}	0.004^{***}	0.003^{**}	0.004^{***}	0.004^{**}	0.005^{***}
	(2.123)	(4.912)	(3.313)	(4.812)	(4.523)	(4.912)
Att	0.004^{*}	0.005^{***}	0.004^{**}	0.005^{***}	0.005^{**}	0.006^{***}
	(2.413)	(5.812)	(4.213)	(5.812)	(3.721)	(6.012)
NSent			0.002^{**}	0.003^{***}	0.003^{**}	0.004^{***}
			(4.312)	(3.812)	(4.623)	(3.812)
Sent × *NSent*					0.006^{**}	0.007^{***}
					(3.001)	(6.223)
Att × *N Sent*					0.007^{**}	0.008^{***}
					(3.623)	(6.812)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.620	0.635	0.630	0.645	0.650	0.665

In contrast, the low ESG group exhibits weaker relationships between *Sent*, *Att*, and market dynamics, with *Sent* coefficients between 0.002 and 0.004, and lower statistical significance. This suggests that low-ESG firms are less responsive to changes in investor sentiment and attention, potentially because of their perceived higher risk or lower investor confidence. The interaction terms between *Sent* and *NSent* and *Att* and *NSent* also show stronger effects in high ESG groups, particularly on volatility, further emphasising the role of ESG factors in amplifying market reactions to sentiment.

5.4. Quantile-on-Quantile Analysis of ESG

The Quantile-on-Quantile (QQ) relationship (please refer to the Appendix on the Journal's website) between aggregate ESG scores and two crucial financial metrics: trading volume and volatility, shows different pattern. As ESG scores increase, particularly in higher quantiles, trading volumes show a marked increase, suggesting heightened investor activity. This pattern indicates that investors may perceive high-ESG firms as more attractive, likely due to perceived lower risk or higher ethical standards, aligning with the signalling theory that suggests that firms with strong ESG performance signal long-term sustainability and stability in the market.

Conversely, it shows a clear inverse relationship between ESG scores and volatility.

Firms with stronger ESG performance tend to experience lower price volatility, which indicates that robust ESG practices contribute to greater market stability. This supports the notion that ESG integration can act as a mitigating factor against market turbulence, potentially because of the more stable investor base and better risk management practices associated with high-ESG firms.

5.5. Robustness Test: Granger Causality and FGLS Regression

Table 6 presents the Granger causality test, which examines the causal relationships between variables. The findings indicate that Investor Sentiment and Investor Attention significantly Granger-cause both Volume and Volatility, demonstrating strong predictive relationships. Specifically, Investor Sentiment shows a significant causal effect on volume with an F-statistic of 4.521 ($p = 0.004$), and on volatility with an F-statistic of 3.945 ($p = 0.050$). Similarly, Investor Attention exhibits significant causality, with F-statistics of 5.103 ($p = 0.002$) for volume and 5.312 ($p = 0.012$) for volatility. News Sentiment also Granger causes both Volume and Volatility, with F-statistics of 4.873 ($p = 0.003$) for volume and 4.729 ($p = 0.003$) for volatility, indicating that media coverage plays a crucial role in shaping market behaviour. Notably, the results indicate that trading Volume and Volatility do not Granger-cause Investor Sentiment, Investor Attention, or News Sentiment, suggesting that these sentiment and attention metrics are exogenous to market movement.

Table 6. Granger Causality Test Results

Causality Direction	F-Statistic	P-Value	Remarks
Investor Sentiment → Volume	4.521	0.004	Reject null, Investor Sentiment Granger causes volume
Volume → Investor Sentiment	2.345	0.098	Do not reject null, No Granger causality
Investor Attention → Volume	5.103	0.002	Reject null, Investor Attention Granger causes volume
Volume → Investor Attention	1.982	0.145	Do not reject null, No Granger causality
News Sentiment → Volume	4.873	0.003	Reject null, News Sentiment Granger causes volume
Volume → News Sentiment	2.125	0.087	Do not reject null, No Granger causality
Environmental → Volume	3.789	0.007	Reject null, Environmental Granger causes volume
Volume → Environmental	1.910	0.152	Do not reject null, No Granger causality
Social → Volume	4.210	0.005	Reject null, Social Granger causes volume
Volume → Social	2.453	0.092	Do not reject null, No Granger causality

Causality Direction	F-Statistic	P-Value	Remarks
Governance → Volume	4.999	0.002	Reject null, Governance Granger causes volume
Volume → Governance	2.812	0.071	Do not reject null, No Granger causality
Investor Sentiment → Volatility	3.945	0.005	Reject null, Investor Sentiment Granger causes volatility
Volatility → Investor Sentiment	2.872	0.061	Do not reject null, No Granger causality
Investor Attention → Volatility	5.312	0.001	Reject null, Investor Attention Granger causes volatility
Volatility → Investor Attention	2.678	0.074	Do not reject null, No Granger causality
News Sentiment → Volatility	4.729	0.003	Reject null, News Sentiment Granger causes volatility
Volatility → News Sentiment	1.756	0.134	Do not reject null, No Granger causality
Environmental → Volatility	3.521	0.009	Reject null, Environmental Granger causes volatility
Volatility → Environmental	2.145	0.104	Do not reject null, No Granger causality
Social → Volatility	4.201	0.005	Reject null, Social Granger causes volatility
Volatility → Social	2.432	0.089	Do not reject null, No Granger causality
Governance → Volatility	4.871	0.003	Reject null, Governance Granger causes volatility
Volatility → Governance	2.834	0.072	Do not reject null, No Granger causality

Table 7 presents the FGLS regression results, addressing heteroskedasticity in the analysis of the impact of different news sentiments (positive, neutral, and negative) on trading volumes and volatility. The results indicate that *Sent* and *Att* exert a more substantial influence under positive and negative news conditions than under neutral news. Specifically, *Sent* demonstrates higher coefficients for trading volume and volatility under positive (0.425 and 0.278) and negative (0.452 and 0.289) news, all significant at the 1% level. This finding suggests that extreme news, whether optimistic or pessimistic, elicits more intense market reactions, leading to greater fluctuations in both trading activities and price volatility.

Att also shows a more pronounced impact under positive and negative news, with coefficients of 0.401 for volume and 0.267 for volatility in the negative news scenario significant at the 1% level. The interaction effects between *Sent* and *NSent* and the interaction effect between *Att* and *NSent* further amplify these impacts, especially under negative news conditions, where these interactions are statistically significant at the 1% level.

Table 7. Regression Results Using FGLS

	Volume			Volatility		
Variables	Positive News	Neutral News	Negative News	Positive News	Neutral News	Negative News
Sent	0.425***	0.398***	0.452***	0.278***	0.252***	0.289***
	(5.320)	(5.543)	(5.784)	(7.671)	(7.982)	(8.445)
Att	0.378***	0.321**	0.401***	0.245***	0.213**	0.267***
	(9.763)	(3.023)	(8.434)	(8.723)	(4.132)	(9.839)
NSent	0.289***	0.265**	0.301***	0.198***	0.176**	0.212***
	(7.415)	(4.983)	(16.72)	(8.132)	(4.435)	(7.738)
Sent × *NSent*	0.357***	0.312*	0.378***	0.289***	0.257*	0.301***
	(8.635)	(2.574)	(21.612)	(8.283)	(2.578)	(7.894)
Att × *NSent*	0.312***	0.298*	0.321***	0.267***	0.245**	0.289***
	(7.162)	(2.594)	(20.124)	(7.172)	(4.748)	(8.445)
Constant	0.028	0.032	0.026	0.017	0.015	0.018
	(1.128)	(1.554)	(1.098)	(1.020)	(0.982)	(1.02)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.620	0.635	0.640	0.655	0.630	0.645

6. Conclusions

This study examines the impact of investor sentiment, investor attention, and news sentiment on trading volumes and volatility within ESG-compliant stocks across three major Asian markets: China, India, and Singapore. The analysis covered a sample of 5,054 companies from 2018 to 2023, employing panel data regression models, quantile-on-quantile regression, Granger causality tests, and FGLS regression.

The results confirmes Hypothesis 1, showing that investor sentiment significantly increases trading volume, particularly in China and Singapore, with a more subdued effect in India. Hypothesis 2, which proposed that investor attention amplifies the effect of sentiment on trading volume, is also supported, especially within high ESG groups. Hypothesis 3, suggesting that news sentiment moderates the relationship between investor sentiment and trading volume, is strongly supported in China and Singapore. Hypothesis 4, which predicts stronger effects in the high ESG groups, is validated, with more pronounced impacts observed in these groups than in the low ESG groups.

6.1. Implications: Theoretical, Managerial and Policy

This study offers several key implications that align with information cascade and signalling theories. In markets with high ESG values, the pronounced effect of investor sentiment suggests that positive ESG performance serves as a strong signal to investors, amplifying their confidence and influencing their trading volumes and volatility. This aligns with signalling theory, where companies with superior ESG performance send positive signals to the market, attracting more investment. Furthermore, the role of news sentiment as a moderator illustrates how the information cascade theory operates, where initial news reports can create a cascade effect that influences subsequent market reactions, particularly in volatile markets.

Managerially, firms with high ESG scores must be strategic in their communication efforts, recognising that their actions and disclosures can trigger significant market reactions. They should consider the potential cascading effects of news and investor sentiment to ensure that their ESG practices are communicated effectively to sustain investor confidence and mitigate market volatility. Policymakers should take concrete action by establishing mandatory ESG reporting standards that require companies to disclose consistent, detailed, and comparable ESG data across industries. This reduces information asymmetry and helps prevent information cascades that can lead to market volatility. Additionally, introducing robust auditing and verification mechanisms for ESG disclosures can ensure the credibility of the information provided, reduce the risk of greenwashing, and foster greater investor trust. Furthermore, incorporating ESG metrics into national and regional risk assessment frameworks would enable more accurate evaluations of long-term financial stability, helping markets respond better to ESG-related risks.

6.2. Limitations and Recommendations

This study is constrained by its reliance on secondary data, which may overlook the qualitative nuances critical for understanding market behaviours influenced by investor sentiment and ESG factors. The use of historical data limits the ability to capture real-time shifts, and a mix of stationary and non-stationary variables can result in spurious regression outcomes. Future research should address this by applying cointegration models or vector error correction models (VECM) to ensure robust long-term relationships between variables. While this study focused on China, Singapore, and India, comparisons with markets such as the US and EU, where ESG frameworks are more developed, would offer broader insights into how regulatory environments shape investor behaviour.

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