Journal of Behavioral and Experimental Finance 37 (2023) 100789

Contents lists available at ScienceDirect

Journal of Behavioral and Experimental Finance

journal homepage: www.elsevier.com/locate/jbef

Full length article

Does investor sentiment influence ESG stock performance? Evidence from India

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ARTICLE INFO

Article history:
Received 29 June 2022
Received in revised form 10 December 2022
Accepted 16 January 2023
Available online 20 January 2023

Keywords:
ESG
Investor sentiment
India
Non-linear cointegration
NARDL
QNARDL

ABSTRACT

This study, for the first time in the literature, investigates the relationship between the ESG index and investor sentiment for an emerging economy, India. The study establishes that the ESG index and investor sentiment are interconnected, but the relationship is asymmetric and inflicted by extreme market conditions. The work reveals that with the boom in the ESG index, investor sentiment weakens and the poor performance of the ESG index stimulates investor sentiment. On the contrary, investor sentiment does not affect the ESG index indicating that the investors are indifferent toward ESG initiatives adopted by the companies. Our results carry insightful implications for policymakers and companies focusing on ESG criteria. The research advances the literature by unveiling that ESG investing is still not well integrated into the Indian investor sentiment and is a far-flung task before it starts impacting the financial markets.

1. Introduction

The last decade witnessed tremendous impetus toward a sustainable investment drive for meeting the environmental, social, and governance (ESG) standards across industries. The "Fossil Fuel Divestment Movement", pledging a divestment of assets over $39.2 trillion, followed by the "Net Zero" commitment in COP26 are some recent remarkable global initiatives for supporting sustainability, which largely rely on corporate actions. On top of the ongoing sustainability tensions, the COVID-19 pandemic has further augmented the focus on the ESG drive (Díaz et al., 2021). Financial institutions are also encouraging sustainability as a priority, compelling corporates to integrate ESG criteria in their strategies (de la Fuente et al., 2021). Subsequently, a significant number of investments have been directed to ESG stocks in recent years (Gao et al., 2022), making them a major portion of global equity portfolios (Daugaard, 2020). Against this backdrop, the big question is whether investors are bothered about this sustainability-related information privilege. Does this information affect investors' beliefs and attitudes towards those companies which adhere to ESG compliances for the betterment of the world? The purpose of the current study is to evaluate if the drive for ESG investment stimulates investor sentiment in the Indian context.

The history of financial crises and stock market crashes has proven the dominant role of investor sentiment on asset pricing and stock markets' efficiency (Economou, 2016), raising doubt on the standard finance models where rational investors equate capital market prices to the present value of expected future cash flows (Baker and Wurgler, 2007). Since the seminal works of De Long et al. (1990) and Shleifer and Vishny (1997), investor sentiment has been widely researched in connection with the stock market (Khan et al., 2020; Li et al., 2022; Le and Luong, 2022), equity market (Islam, 2021), cryptocurrency market (Naeem et al., 2021) and the green industry stock prices (Piñeiro-chousa et al., 2021; Wang et al., 2021). Indian stock market is also not insulated from investor sentiment, as established by Paramanik and Singhal (2020) and Haritha and Rishad (2020). Thus, investor sentiment plays a prominent role in the financial markets and ESG being one of the most canvassed emerging asset classes, might not be immune from its influence.

ESG ratings and ESG scores represent a firm's ESG performance. The ESG scores are consolidated to create a country's ESG index, which tracks the ESG performance of all the top players in the financial market.[4] The majority of literature focuses on the firm-level ESG performance measured as ESG scores or ratings.

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4 Please refer to Section 2 to understand how ESG Scores converge to ESG Ratings for NSE and MSCI.

https://doi.org/10.1016/j.jbef.2023.100789

For instance, Fatemi et al. (2018), Yoo and Managi (2021) and Chen and Xie (2022) establish the importance of ESG activities, disclosures in strengthening a firm's value and overall corporate financial performance. Giudice and Rigamonti (2020) highlighted the auditing quality of sustainability reporting to augment the reliability of firms' ESG scores. Studies (Citterio and King, 2023; De Spiegeleer et al., 2021; Eliwa et al., 2021; Li et al., 2022) have also examined the role of ESG scores & ratings for lending institutions and portfolio allocation. Li et al. (2022) found that ESG ratings reduce a firm's default risk and Eliwa et al. (2021) used both, ESG scores and ratings (as performance and disclosure measures) to ascertain their relationship with the cost of debt. Citterio and King (2023) establish that ESG factors improve the predictability of banks' financial distress for EU countries. De Spiegeleer et al. (2021) incorporate ESG criteria in the allocation of equity portfolios and reveal that the ESG rating data analysis does not provide clear-cut evidence for enhanced performance of portfolios with either high or low ESG scores of US and European companies. Khemir et al. (2019) expose that ESG information influences the investment allocation decisions in an emerging economy like Tunisia where governance & social information play an influential role over environmental information. Interestingly, based on bibliometrics and meta-analysis, Khan (2022) concludes that the link between a firm's financial performance and ESG is still inconclusive. But Khan (2022)'s outcome has not discouraged researchers in venturing other intricacies of firm-level ESG research. These studies investigate how good and bad news influence ESG rated firms. For example, Sabbaghi (2022) found that the volatility of ESG firms is larger for bad news, compared to good news. Chen and Yang (2020) establish similar findings for Taiwan where investors exhibit optimism(pessimism) for companies with higher (lower) ESG scores.

ESG as an asset class has also attained tremendous attention among researchers. In the last few years, many studies have explored the linkages between the ESG index and other conventional asset classes traded in the stock market. Andersson et al. (2020) examined the causal link of the world ESG index with currency, commodity and stock markets. The study shows that ESG portfolio returns influence currency and commodity returns. Plastun et al. (2022) find that price effects of one-day abnormal return are not significantly different for conventional and ESG indices, across developed and emerging countries. While examining the volatility risk spillover among worldwide ESG leaders' equity markets, Chen and Lin (2022) established that the Northern American (NA) and E.U. markets are the main risk transmitters to the global ESG investment market. The study corroborates the results of Gao et al. (2022) for the NA region. Kilic et al. (2022) studied the interdependence between conventional and ESG stocks for thirty-eight developing and developed countries who found positive (negative) co-movements of ESG returns with the conventional stock returns for developing (developed) countries. Naeem et al. (2023), while studying the ESG indices for four regional markets, establish that the COVID-19 outbreak created arbitrage opportunities in the US, Latin America, and Asia-Pacific regions but not for Europe.

Surprisingly, in this plethora of ESG-related empirical research, studies examining the linkage between the ESG index and investor sentiment index, which represents firms' activities in the financial market, are almost non-existent. Some recent studies indicate the diversification potential of ESG investments by examining how COVID induced panic index (Umar and Gubareva, 2021) and social media coverage of the COVID pandemic (Umar et al., 2021) influence the ESG index's volatility for US, Europe and emerging markets. A couple of studies (Ford et al., 2022; Vuong, 2022) explore investor sentiment angle with ESG ratings or scores at the company level. The former studied whether ESG ratings are influenced by the sentiment of options traders for US companies operating in industries like materials, consumer discretionary, communications, utilities, and real estate sectors. The finding indicates investors' optimistic sentiment is driven by the highest-rated ESG portfolio. The put–call ratio is the sentiment proxy. Vuong (2022)'s study advocates the moderating role of investor sentiment in the link between the corporate social responsibility (CSR) and financial performance (FP) of 367 Japanese companies. ESG scores are used as a proxy for CSR. The investor sentiment used here is firm-specific sentiments, proxied by previous six-month cumulative stock returns and market sentiment constructed from consumer confidence index, volatility index, and advance/decline ratio. The study infers that the ESG–FP relationship weakens under the moderating influence of investor sentiment.

Therefore, it is evident that so far, the investigation of a dynamic chronological relationship between the ESG index and investor sentiment remains unexplored. The current study addresses this knowledge gap by constructing a sentiment index based on 10 sentiment proxies and evaluating its dynamic causal relationship with ESG Index. Our study uses market-based indicators of firms' activities like performance, liquidity, financing activities, options trading, trading activity and enthusiasm, evolving over time to develop a sentiment index (Kumari, 2019; Kumari and Mahakud, 2016, 2015). These indicators are adjusted to remove the confounding effects of macroeconomic fundamentals like economic activity, inflation, interest rates, term spreads, exchange rates, and foreign institutional investments to obtain a holistic representation of investor sentiment in Indian financial markets. An ESG Index reflects the ESG initiatives of major financial market participants of a country. For example, the Nifty 100 ESG Index is derived from the NIFTY 100 Index companies. Since our sentiment index represents the market activities of major corporates in the financial market, it is logical to explore if the thrust for ESG performance of corporates is linked with this market-oriented investor sentiment. The outcomes can help in evaluating the investor sentiment towards ESG initiatives of Indian corporates and devise strategies accordingly.

Thus, the novelties of the paper are as follows:

1. Our study is based in India and is well-timed. The country is struggling to achieve its Sustainable Development Goals (SDGs) (Sachs et al., 2021) and its government policies & regulations are rigorously trying to encourage sustainability. The major securities markets of India offer a variety of sustainability-themed indices.[5] The study has used the NIFTY 100 ESG Index (ESG_ NSE) to capture the ESG reporting by Indian companies. The study has also used MSCI India ESG Leaders Index (ESG_MSCI) to validate the empirical findings.
2. In this study, we create a sentiment index following the works of Brown and Cliff (2004), Baker and Wurgler (2006), Baker and Wurgler (2007), Kumari and Mahakud (2015), and Kumari (2019). Our sentiment index is different from Ford et al. (2022) and Vuong (2022). The former focused on sector-specific option traders' sentiment index whereas Vuong (2022)'s sentiment index is firm-specific and limited to 367 Japanese firms only. Moreover, both studies use panel data analysis and thereby ruling out the possibilities of reverse causality between ESG scores and investor

[5] India has seven active stock exchanges as reported by SEBI on January 17, 2020. The two major exchanges offering the mentioned ESG indices are Bombay Stock Exchange (BSE) and National Stock Exchange (NSE), namely, S&P BSE 100 ESG Index, S&P BSE CARBONEX, S&P BSE GREENEX, NIFTY100 ESG, NIFTY100 Enhanced ESG and Nifty100 ESG Sector Leaders Index. Along with these, MSCI also offers sustainability and ESG related indices for India.

sentiment. In contrast, we used 10 sentiment proxies to represent the market activities of corporates and investors to holistically capture all aspects of financial markets.

3. So far as empirical analysis is concerned, earlier ESG-related studies (Andersson et al., 2020; Chen and Yang, 2020; Kilic et al., 2022; Naffa and Fain, 2021) used return series instead of level variables, thereby negating the possibility of cointegration or a long-term equilibrium relationship among the variables. This approach is theoretically incongruent (Yahya et al., 2021), and needs a careful revisit of the prevalent modeling strategies. Our model includes four variables (two primary and two control) in their level forms while testing the long-run relationship to prevent any information loss arising from the transformation of level variables.
4. We apply cointegration techniques that capture the non-linear asymmetric relationship between the ESG and investor sentiment indices in different market conditions. The asymmetric behavior of non-linearity is explored by employing a Non-Linear Autoregressive Distributed Lag (NARDL) model of cointegration developed by Shin et al. (2014), which is further supplemented by a Quantile NARDL (Cho et al., 2015) to examine extreme patterns in the asymmetric relationship. To further strengthen the connectedness between these two variables, we consider the economic policy uncertainty index (PUI) and the Indian market volatility index (VIX) as control variables.

Our study establishes a long-term link (cointegration) between the ESG and investor sentiment indices, which is asymmetric and quantile dependent, demonstrating extreme behavioral patterns. Based on the results obtained from both the models (NARDL and QNARDL), we found that increase(decrease) in the ESG index weakens(strengthens) investor sentiment. On the contrary, as against conventional wisdom, investor sentiment does not affect the ESG index. QNARDL results also suggest that the higher ESG index negatively influences investor sentiment. But the impact is maximum when the investor sentiment index scores high. Additionally, QNARDL results exhibit that the ESG index can stimulate investor sentiment in the long run, even though not instantaneously. These results are validated using the MSCI ESG index, strengthening empirical findings.

Our study supports the findings of Dyck et al. (2019), who found that firms' environmental and social (E&S) performance in 45 developed and developing countries does not depend on institutional investors, especially in those countries where E&S norms are weak. The current work contradicts previous studies (Chen and Yang, 2020; Ford et al., 2022; Vuong, 2022) which advocate the influence of investor sentiment on ESG scores for the firms located in Taiwan, the US, and Japan, respectively. Our findings also differ from earlier studies (Haritha and Rishad, 2020; Khan et al., 2020; Paramanik and Singhal, 2020; Piñeiro-chousa et al., 2021; Wang et al., 2021) which advocated the influence of investor sentiment in the financial markets.

The results of our study signal investor's indifference towards ESG aspects in India, posing a serious breach in the purpose of ESG reporting and a dire need to revisit the ESG policies and approach. This could be due to the compromise they might have to make with their profit motive, along with the fear of being cheated by dishonest claims. The COP27 report strongly criticized greenwashing, which not only discredits genuine philanthropic corporates and misleads primary stakeholders, but also annihilates the very purpose of ethical business practices. Our results further intensify the responsibility of the regulators and sustainability promoters (organizations), as they need to work on three different sides: motivate the profit-driven corporates to encompass ESG initiatives in their actions; promote ESG accounting along with preventing greenwashing for existing compliant companies; and communicating these efforts and their importance to the investors.

Our paper is further followed by a brief explanation of the data and variables in Section 2. It is then followed by a discussion on methodology (Section 3), including the sentiment index creation methodology in Section 3.1 and the four models applied in the study. Section 4 discusses the empirical outcomes. Section 5 concludes the study.

2. Data and variables

This study employs the NIFTY 100 ESG Index (ESG_NSE) to measure the ESG performance of Indian companies. It is selected as a representative of India's ESG performance as it is reported by the leading stock exchange of the country (National stock exchange of India) and is also available for a longer period (as opposed to S&P BSE 100 ESG Index, launched in 2017). MSCI INDIA ESG Leaders Net Total Return[6] USD Index (ESG_MSCI), a popularly used ESG measure by researchers and practitioners worldwide, is also analyzed to validate the findings. ESG_NSE picks out companies with high ESG scores (assessed by Sustainalytics) from the NIFTY 100 index (Methodology Document for Equity Indices, 2022), and ESG_MSCI picks out companies with high ESG scores (assessed by MSCI ESG Research Inc) from the MSCI Global Investable Market Indices (MSCI ESG Ratings Methodology, 2020).

For creating the sentiment index (SENT), ten sentiment proxies and six orthogonalization proxies are used following Kumari and Mahakud (2016, 2015) and Kumari (2019). Table 1 lists the variables used for creating SENT. The rationale and methodology deployed in preparing the SENT variable are discussed in Section 3.1. Please note that each sentiment proxy represents some aspects of the market. For instance, ADR and BSI incorporate market performance, TV and TVR represent market liquidity, IPO indicates enthusiasm, E indicates financing activities, Div. P represents future prospects, PCR captures the sentiment in the options trading market, FF represents mutual fund activity and Δ Margin represents the type of trading activity (Kumari and Mahakud, 2016). Thus, these sentiment proxies comprehensively cover almost all aspects of financial markets. Since all these sentiment proxies are derived from or represent the Indian financial market, they are bound to be influenced by the economic circumstances, as well as the business cycle fluctuations of the country. Therefore, to get rid of the impact of such macroeconomic fluctuations, these proxies have been orthogonalized using a set of 6 macroeconomic variables (hence referred to as orthogonalization proxies) (Baker and Wurgler, 2006). In the obtained time series, the SENT index exhibits bullish and bearish sentiments of investors (Kumari and Mahakud, 2016, 2015).

Our study employs the market volatility index (VIX) and economic policy uncertainty (PUI) to control for the effect of the economic and market ambiguity on them while investigating the relationship between investor sentiment and the ESG index. Economic policy uncertainty shows a positive link with ESG performance (Shaikh, 2021; Vural-Yavaş, 2021) and investor sentiment has a natural influence on the market volatility index (Kumari, 2019; Xu et al., 2019). India's PUI has been adopted from Baker et al. (2016) based on policy-related economic uncertainty in newspapers. It represents various macro and micro variables,

[6] MSCI offers three index variant types using 2 methodologies: (i) based on price adjustment factor (STRD); (ii) based on total return (NETR and GRTR). The word "Return" here does not refer to a difference series, these indices measure the market performance "including price performance and income from regular cash distributions" (MSCI Index Calculation Methodology, 2012).

Table 1
Variables used in the sentiment index.

S. No.	Type	Proxy Variable	Description	Source
1	Sentiment proxies	ADR	Advances and decline ratio	NSE India
2		BSI	Buy and sell imbalance	Bloomberg
3		TV	Trading volume	Bloomberg
4		TVR	Turnover volatility ratio	Bloomberg
5		IPO	Initial Public Offers (Volume)	Sebi
6		E	Equity issues in a total of equity and debt	Sebi
7		Div. P	Market to book ratio of dividend payers and nonpayers firms	CMIE Prowess IQ
8		PCR	Put call ratio	Bloomberg
9		FF	Fund Flow	Bloomberg
10		Δ Margin	Security lending and borrowing	NSE India
1	Orthogonalization Proxies	IIP	Index of industrial production as proxy of economic growth	Bloomberg
2		TBR	Short term interest rates as treasury bill rates	
3		TS	Term spread (difference between long term bond yield and treasury bill rate)	
4		EX	Exchange rate	
5		WPI	Wholesale price index (as a proxy of rate of inflation)	
6		FII	Foreign institutional investments	

Notes: (1) Author's list of variables and their sources, used for creating the sentiment index based on Kumari and Mahakud (2015) and Kumari (2019). (2) Orthogonalization proxies are macroeconomic variables, employed in the orthogonalization process of the sentiment proxies.

Table 2
Statistical properties.

	SENT	ESG_NSE	ESG _MSCI	PUI	VIX
Mean	0.0119	1625.938	1562.521	100.0375	18.2199
Median	−0.0747	1545.985	1479.045	82.1312	16.8200
Maximum	4.0959	3221.300	2808.780	283.6891	64.4075
Minimum	−5.5671	767.6600	891.0500	32.8836	10.8600
Std. Deviation	1.2536	574.7948	458.2894	53.2062	6.4206
Skewness	−0.3151	0.5807	0.7085	1.3272	3.4294
Kurtosis	5.6766	2.8953	3.0256	4.5782	23.1107

Notes: Authors' calculation. ***, **, and * represent 1%, 5%, and 10% statistical significance.

such as stock price volatility, investment and employment (Baker et al., 2016). The Indian market volatility index (VIX) is the next 30-day volatility expectation of the Nifty option prices and is the trademark VIX of the Chicago Board Options Exchange (India VIX Index*, 2021). It measures conditional variance (Kanas, 2012) and represents market fear and volatility (Hkiri et al., 2018). PUI has been obtained from Policy Uncertainty Index's website (Baker et al., 2022); ADR (Table 1) has been obtained from the National Stock Exchange of India's website (NSE, 2022); IPO and E (Table 1) are sourced from The Securities and Exchange Board of India's (SEBI, 2021) and Div. P (Table 1) information has been derived from the CMIE Prowess I.Q. Database. The rest of the time series are obtained from the Bloomberg database.

The study employs monthly data from April 2011 to July 2021. Since the ESG index is not available before April 01, 2011 (IISL, 2018), we used April 2011 as the starting point of our analysis. Further, the data frequency is selected at a monthly level for two reasons. First, some of the sentiment proxies (such as Initial Public Offers (IPO), Equity issues in a total of equity and debt (E), Market to book ratio of dividend payers and nonpayers firms (Div.P)) are only available at monthly frequency. Secondly, some macroeconomic variables used to remove the bias of sentiment proxies (IIP, WPI) and the control variable economic policy uncertainty index are also available monthly. Since the sentiment index is developed on a monthly frequency, the ESG index is also considered on a monthly level. Kumari (2019) and Kumari and Mahakud (2016, 2015) also used monthly frequency in their index creation for the Indian economy due to the same reason.

Table 2 presents the statistical properties of the data used in the model. The majority of the variables show a departure from normality. For example, VIX shows an extreme leptokurtic behavior with a very high positive excess kurtosis of 20.1107 (=23.1107–3), indicating its vulnerability to be affected by extreme tails. The finding is intuitive as VIX indicates the volatility of financial markets. SENT and PUI also demonstrate a heavy tail distribution with excess kurtosis of 2.6766 and 1.5782 respectively. In contrast, ESG indices, ESG_NSE and ESG_MSCI demonstrate a minor departure from normality. ESG_NSE has a platykurtic pattern with a negative excess kurtosis of −0.1047 which implies less chance of experiencing extreme returns. ESG_MSCI has the closest proximity to normality with excess kurtosis of 0.0256 only. Thus, the summary indicates that the relationship between investor sentiment and the ESG index in the presence of two control variables VIX and PUI cannot be investigated in the conventional linear framework that evolves around the mean or median. The chronological representation of these variables is shown in Appendix (Fig. A.2) to maintain brevity.

3. Material and methods

3.1. Sentiment index

Researchers have attempted to measure investor sentiment using various methods, majorly including surveys (Buchheim et al., 2022; Gric et al., 2022; Woldeamanuel and Nguyen, 2018), text analysis or opinion mining (Alamoodi et al., 2021; Chalkiadakis et al., 2022; Chang et al., 2022; Kim et al., 2022), ready-made proxies and indices (Bennani, 2020; Fisher and Statman, 2003, 2000; Mokni et al., 2022; Rakovská, 2021; Tiwari et al., 2022; Wang, 2018) and custom-made indices (Baker and Wurgler, 2006; Bathia and Bredin, 2018; Brown and Cliff, 2004; Lee et al., 2002). They are also performing various Aspect-Based Sentiment Analyses to narrow down sentiments (Ganganwar and Rajalakshmi, 2019). So, though quantifying investor sentiment is a complicated and debatable task, seminal works of Brown and Cliff (2004), Baker and Wurgler (2007, 2006) and Baker et al. (2012) have largely simplified the complex process of measuring custom-made investor sentiment. These studies used a set of sentiment proxies and macroeconomic variables to capture investor sentiment. Since then, researchers (Chen et al., 2021; Cheong et al., 2017; He, 2020; Le and Luong, 2022; Long et al., 2021; Wang et al., 2021) have widely adopted this methodology. In the Indian context, Kumari and Mahakud (2016, 2015) and Kumari (2019) are worth mentioning as they modified the variables to suit the requirement of the Indian economy while constructing investor sentiment.

The current study intends to evaluate if the drive for ESG efforts has any influence on investor sentiment and as a feedback channel whether investor sentiment boosts ESG performance. In India, the ESG index, traded in major stock exchanges, captures the performance of all the top players of the financial market in ESG-related phenomena. The Indian market is dominated by institutional investors (OECD, 2020). In the current context, we adopt a custom-made investor sentiment index following Kumari (2019) and Kumari and Mahakud (2016, 2015), so that the market activities of corporates and investors, can be encapsulated exhaustively exhibiting all aspects of financial markets. Although ESG is a relatively new concept in the financial market, the enormous push for ESG efforts across all sectors should ideally reflect in market activities. Thus, examining the link between the ESG index and a market-indicator-based investor sentiment is sensible in the current context. We consider ten sentiment proxies (Kumari (2019) and Kumari and Mahakud (2015)) to better reflect the investor sentiment for the Indian context. Additionally, we use six macroeconomic indicators to eliminate the possible confounding effect of these economic fundamentals on the sentiment proxies.[7]

The creation of the sentiment index is a four-step strategy. Step 1 involves the orthogonalization of the sentiment proxies. The process aims at arriving at an impeccable investor sentiment by removing the impact of economic events or business cycle variations from the sentiment variables. The ten residual series, obtained by estimating linear regressions of each sentiment proxy as a function of six fundamental variables (Eq. (1)) represent the orthogonalized sentiment proxies.

$$SENT_{it} = \alpha_0 + \alpha_{01} \sum_{j=1}^{j} FUND_{jt} + \varepsilon_{it} \tag{1}$$

where $SENT_{it}$ represents each of the sentiment proxies, $FUND_{jt}$ represents each of the fundamental variables, and ε_{it} represents the error term, which is the irrational component of the related sentiment proxy. The values obtained from the regression for each of the proxies (fitted values) represent the rational component of the respective proxy. The error term obtained ε_{it} represents the adjusted sentiment proxies and is used in further steps.

In the second stage, we apply Principal Component Analysis (PCA) to these ten adjusted sentiment proxies or residuals obtained from step 1, and the one-period lagged variables of these adjusted series. The rationale for incorporating one-period lagged variables is guided by the embedded persistent effect of sentiment proxies (Baker and Wurgler, 2006). Since the first component captures the maximum explanatory power of the variables, we choose the first principal component[8] as the proxy of the common investor sentiment index (Baker and Wurgler, 2006, 2007; Brown and Cliff, 2004). It represents a first-stage sentiment index series.

The third step includes obtaining a correlation matrix of the first stage index series (obtained in the previous step) and all the leads and lags of the ten adjusted sentiment proxies (from the first step). We then select sentiment proxies, either the lead or the lagged variable, which show a statistically significant correlation with the first stage index. For example, if the sentiment variables IPO_t and IPO_{t-1} have high correlations with the first PCA, we select only one basis of its statistical significance. In this way, we build a set of ten sentiment proxies.

Finally, we re-apply the PCA to the sentiment proxies derived in the previous step. The first PCA obtained from this stage represents the sentiment index (SENT) for our analysis. The obtained PCA series explains little less than 50% variance.

The sentiment index, SENT, is derived using the given equation after following the above-discussed steps:

$$\begin{aligned} SENT_t = & -0.5987ADR_{t-1} - 0.1751BSI_t + 0.3168TV_t \\ & + 0.3192TVR_t + 0.3192IPO_t + 0.02611E_t \\ & + 0.0779DIV.P_t + 0.3245PCR_t \\ & + 0.1093FF_{t-1} + 0.4722\Delta Margin_{t-1} \end{aligned} \tag{2}$$

3.2. Non-linear the Autoregressive Distributed lag (NARDL) model of cointegration

The cointegration is a systematic co-movement of two or more non-stationary series. Engle and Granger (1987) showed that if the two series X and Y (say) are individually integrated of order one i.e. I(1) in nature and share a common stochastic trend then there exists a long-run relationship among the variables or, in other words, variables are cointegrated. Since the seminal works of Engle and Granger (1987), Johansen and Juselius (1990) and Pesaran et al. (2001) these linear cointegration methods are extensively used in empirical research. Pesaran et al. (2001)'s method of Autoregressive-Distributed lag (ARDL) bounds tests approach for cointegration is employed regardless of whether the underlying variables are stationary i.e. $I(0)$, integrated of order one i.e. $I(1)$ or fractionally integrated. But this approach ignores the possibilities of asymmetries in variables. Shin et al. (2014)'s NARDL framework is an extension of Pesaran et al. (2001) 's ARDL model that overcomes the assumption of linearity while incorporating asymmetries or positive and negative partial sums of study variables. Since we are examining the relationship of the variables having I(1) and I(0) combination, the NARDL model is possibly the most suited in the current context.

The general form of a NARDL model is:

$$\begin{aligned} \Delta Y_t = & \alpha_{0Y} + \sum_{i=1}^{n} \alpha_{1iY} \Delta Y_{t-1} + \sum_{i=1}^{n} \alpha_{2iY}^{+} \Delta X_{1t-i}^{+} + \sum_{i=1}^{n} \alpha_{2iY}^{-} \Delta X_{1t-i}^{-} \\ & + \sum_{i=1}^{n} \alpha_{3iY}^{+} \Delta X_{2t-i}^{+} + \sum_{i=1}^{n} \alpha_{3iY}^{-} \Delta X_{2t-i}^{-} + \omega_{1Y} Y_{t-1} + \omega_{2Y}^{+} X_{t-1}^{+} \\ & + \omega_{2Y}^{-} X_{t-1}^{-} + \omega_{3Y}^{+} X_{2t-1}^{+} + \omega_{3Y}^{-} X_{2t-1}^{-} + \psi_{1t} \end{aligned} \tag{3}$$

where Δ is the first difference operator. ω and α represent long- and short-run coefficients, respectively, for positive and negative partial sums, represented as superscripts, for lag years. Both long- and short-run asymmetries are tested using the standard Wald test (Shin et al., 2014). The null hypothesis for short-run asymmetry is:

H_0: $\sum_{i=0}^{n} \alpha_{jy}^{+} = \sum_{i=0}^{n} \alpha_{jy}^{-}$; where j=1

The null hypothesis for long-run symmetry is

$\delta^{+} = \delta^{-}$; where $\delta^{+} = \frac{-\omega_{jy}}{\omega_{1Y}}$ and $\delta^{-} = \frac{-\omega_{-jy}}{\omega_{1Y}}$; where j=1.

This study tests the non-linear long- and short-run relationship between ESG and SENT indices in the presence of two control variables, PUI (policy uncertainty) and VIX (Volatility Index).

[7] Following Baker and Wurgler (2006) we have limited orthogonalization proxies to macroeconomic variables only and not used the additional market orthogonalization proxies used by Kumari and Mahakud (2015).

[8] A linear combination of lead and one-period lagged sentiment proxies.

We have created the following four models (M1, M2, M3 and M4), testing the investor sentiment index (SENT) separately with ESG_NSE and ESG_MSCI. Keeping in mind the scope of our study, the asymmetry in variables is tested to the SENT and ESG variables and not to control variables, PUI and VIX. The equations of the NARDL models tested for this study are:

M1: F(SENT/ESG_NSE(+), ESG_NSE (-), PUI, VIX)

$$\begin{aligned}\Delta SENT_t &= \alpha_{0SENT} + \sum_{i=1}^{n} \alpha_{1iSENT}\,\Delta SENT_{t-1} \\ &+ \sum_{i=1}^{n} \alpha^{+}_{2iSENT}\,\Delta ESG\_NSE^{+}_{i,t-1} \\ &+ \sum_{i=1}^{n} \alpha^{-}_{2iSENT}\,\Delta ESG\_NSE^{-}_{i,t-1} + \sum_{i=1}^{n} \alpha_{3iSENT}\,\Delta VIX_{i,t-1} \\ &+ \sum_{i=1}^{n} \alpha_{4iSENT}\,\Delta PUI_{i,t-1} + \omega_{1SENT} SENT_{t-1} \\ &+ \omega^{+}_{2SENT} ESG\_NSE^{+}_{i,t-1} + \omega^{-}_{2SENT} ESG\_NSE^{-}_{i,t-1} \\ &+ \omega_{3SENT} VIX_{i,t-1} + \omega_{4SENT} PUI_{i,t-1} + \psi_{1t} \end{aligned} \tag{4}$$

M2: F(SENT/ESG_MSCI(+), ESG_MSCI(-), PUI, VIX)

$$\begin{aligned}\Delta SENT_t &= \alpha_{0SENT} + \sum_{i=1}^{n} \alpha_{1iSENT}\,\Delta SENT_{t-1} \\ &+ \sum_{i=1}^{n} \alpha^{+}_{2iSENT}\,\Delta ESG\_MSCI^{+}_{i,t-1} \\ &+ \sum_{i=1}^{n} \alpha^{-}_{2iSENT}\,\Delta ESG\_MSCI^{-}_{i,t-1} \\ &+ \sum_{i=1}^{n} \alpha_{3iSENT}\,\Delta VIX_{i,t-1} + \sum_{i=1}^{n} \alpha_{4iSENT}\,\Delta PUI_{i,t-1} \\ &+ \omega_{1SENT} SENT_{t-1} + \omega^{+}_{2SENT} ESG\_MSCI^{+}_{i,t-1} \\ &+ \omega^{-}_{2SENT} ESG\_MSCI^{-}_{i,t-1} + \omega_{3SENT} VIX_{i,t-1} \\ &+ \omega_{4SENT} PUI_{i,t-1} + \psi_{1t} \end{aligned} \tag{5}$$

M3: F(ESG_NSE/ SENT(+), SENT(-), PUI, VIX)

$$\begin{aligned}\Delta ESG\_NSE_t &= \alpha_{0ESG\_NSE} + \sum_{i=1}^{n} \alpha_{1iESG\_NSE}\,\Delta ESG\_NSE_{t-1} \\ &+ \sum_{i=1}^{n} \alpha^{+}_{2iESG\_NSE}\,\Delta SENT^{+}_{i,t-1} \\ &+ \sum_{i=1}^{n} \alpha^{-}_{2iESG\_NSE}\,\Delta SENT^{-}_{i,t-1} \\ &+ \sum_{i=1}^{n} \alpha_{3iESG\_NSE}\,\Delta VIX_{i,t-1} + \sum_{i=1}^{n} \alpha_{4iESG\_NSE}\,\Delta PUI_{i,t-1} \\ &+ \omega_{1ESG\_NSE} ESG\_MSCI_{t-1} + \omega^{+}_{2ESG\_NSE} SENT^{+}_{i,t-1} \\ &+ \omega^{-}_{2ESG\_NSE} SENT^{-}_{i,t-1} + \omega_{3ESG\_NSE} VIX_{i,t-1} \\ &+ \omega_{4ESG\_NSE} PUI_{i,t-1} + \psi_{1t} \end{aligned} \tag{6}$$

M4: F(ESG_MSCI/ SENT(+), SENT(-), PUI, VIX)

$$\begin{aligned}\Delta ESG\_MSCI_t &= \alpha_{/0ESG\_MSCI} + \sum_{i=1}^{n} \alpha_{1iESG\_MSCI}\,\Delta ESG\_MSCI_{t-1} \\ &+ \sum_{i=1}^{n} \alpha^{+}_{2iESG\_MSCI}\,\Delta SENT^{+}_{i,t-1} \\ &+ \sum_{i=1}^{n} \alpha^{-}_{2iESG\_MSCI}\,\Delta SENT^{-}_{i,t-1} \\ &+ \sum_{i=1}^{n} \alpha_{3iESG\_MSCI}\,\Delta VIX_{i,t-1} \\ &+ \sum_{i=1}^{n} \alpha_{4iESG\_MSCI}\,\Delta PUI_{i,t-1} \\ &+ \omega_{1ESG\_MSCI} ESG\_MSCI_{t-1} + \omega^{+}_{2ESG\_MSCI} SENT^{+}_{i,t-1} \\ &+ \omega^{-}_{2ESG\_MSCI} SENT^{-}_{i,t-1} + \omega_{3ESG\_MSCI} VIX_{i,t-1} \\ &+ \omega_{4ESG\_MSCI} PUI_{i,t-1} + \psi_{1t} \end{aligned} \tag{7}$$

3.3. *Quantile NARDL model of cointegration*

The NARDL model gives us the non-linear and asymmetric relationship among the variables, and the quantile regression model further explains the non-linearity among the variables by moving away from the conditional mean and describing the relationship amongst the variables at different quantiles of the dependent variable. The combination of these two methodologies gives us QNARDL (Cho et al., 2015), which enables us to test distributional asymmetry.

The model can be represented by the following mathematical equation:

$$\begin{aligned}Q_{\Delta Yt} &= \rho_0(\tau) + \rho_Y(\tau)\,Y_{t-1} + \rho_s^{+}(\tau)\,X^{+}_{t-1} \\ &+ \rho_s^{-}(\tau)\,X^{-}_{t-1} + \sum_{i=1}^{p-1} \alpha_i(\tau)\,\Delta Y_{t-1} \\ &+ \sum_{i=0}^{q-1} (\theta_i^{+}(\tau)\,\Delta X^{+}_{t-1} + \theta_i^{-}(\tau)\,\Delta X^{-}_{t-1} + \varepsilon_t(\tau)) \end{aligned} \tag{8}$$

In the above equation, τ represents each quantile of the dependent variable in a way that $0 < \tau < 1$. We have chosen five quantiles, 10%, 25%, 50%, 75% and 90%, based on the distribution of dependent variables. In addition to long- and short-run asymmetries, the model also tests distributional asymmetry (Al-Khazali et al., 2018) of the independent variable on the dependent variable. The distributional asymmetry is tested using a Wald test of the null hypothesis. In model M1, the null hypothesis of distributional asymmetry of $SENT_{t-1}$ on Δ SENT is:
$\rho_{SENT}(0.10) = \rho_{SENT}(0.25) = \rho_{SENT}(0.50) = \rho_{SENT}(0.75) = \rho_{SENT}(0.90)$

Similar hypotheses are tested for the other three models, M2, M3, and M4.

4. Results and discussions

The section discusses the stationarity properties of the variables. Based on the unit root test results, we have addressed non-linearity in the cointegration relationship between investor sentiment and the ESG index from the angle of asymmetry (NARDL) and distribution asymmetry or tail dependence (QNARDL). A comprehensive modeling strategy adopted in this study is explained in Fig. A.1 for ready reference.

4.1. *Unit root tests*

We apply both conventional and structural breaks unit root tests to examine the stationarity property. While SENT, VIX, and PUI are I(0) variables, both the ESG variables (ESG_NSE, ESG_MSCI) are I(1) in nature (Table 3). So, we have a combination

Table 3
Unit root tests.

Variables	ADF	PP	KPSS
	Level		
SENT	−12.549**	−12.467**	0.144
ESG_NSE	−1.510	−1.580	0.087
ESG_MSCI	−2.474	−2.474	0.129
VIX	−5.743**	−5.676**	0.206**
PUI	−3.318	−5.070**	0.233**
	First Difference		
SENT	NA	NA	NA
ESG_NSE	−10.775**	−10.775**	NA
ESG_MSCI	−12.323**	−12.370**	NA
VIX	NA	NA	0.237
PUI	−11.687**	NA	0.154

Note: '**' imply a level of significance at 5%. The Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests for the non-stationarity property of the series. NA: Not applicable

Table 4
Unit root tests with structural breaks.

Variables	Bai and Perron		
	F-Stat	UDMax	WDMax
SENT	21.519**(5)	37.796**(1)	37.796**(1)
ESG_NSE	14.591**(5)	8.943 (0)	14.591**(5)
ESG_MSCI	13.162**(5)	9.673(0)	13.272**(3)
VIX	17.058**(5)	11.003(0)	17.553**(4)
PUI	15.858**(5)	26.941**(1)	26.941**(1)

Notes: () indicates breakpoints. '**' shows statistical significance at 5% level.

of both stationary and non-stationary variables indicating the suitability of the ARDL model (Pesaran et al., 2001).

The Bai & Perron (B.P.) unit-root test (Bai and Perron, 1998, 2003, 2003) with multiple breakpoints confirm the presence of structural breaks across all variables (Table 4), suggesting the presence of non-linearity of the variables. Thus, the NARDL model is more appropriate in the current context.

4.2. NARDL cointegration test

To examine the asymmetry in the long-run relationship between ESG and SENT indices, we first apply the NARDL bounds test. In the next step, the NARDL model is estimated to examine long-and short-run dynamics of these variables.[9]

The NARDL Bounds test for cointegration shows a rejection of the null hypothesis of no cointegration for four models (M1 to M4), since F-Statistics fall beyond the upper bound critical value for a 5% level of significance (Table 5). This confirms the presence of a non-linear asymmetric cointegrating relationship between SENT and ESG indices. SENT and ESG indices share a long-run equilibrium relationship but respond differently to positive and negative changes in the explanatory variables. Moreover, the relationship appears to be stronger when SENT is the dependent variable.

4.3. NARDL estimation results

As the next step, we estimate NARDL models for ESG and SENT separately (Table 6). Results for ESG_MSCI and SENT (Models, M2 and M4) are kept in the Appendix (Table A.1) for brevity. The MSCI ESG index is mainly used for validation purposes.

Before analyzing the long- and short-run dynamics of these models, a few diagnostics like the Wald test of asymmetry and the model stability are examined. The lagged dependent variables on models M1 and M3, representing the speed of adjustment, are statistically significant and negative, indicating the validity of the NARDL estimation results. The Wald asymmetry test is rejected for model M1 but not for model M3 at a 5% level of significance. It implies that the positive or negative effects of ESG_NSE impact the SENT asymmetrically. However, the contrary effect is not statistically significant, signaling the immutability of the investor sentiment index over the ESG index. Outcomes re-confirm the evidence obtained in Table 5, where SENT shows a strong bond with ESG_NSE when the former is a dependent variable. Similar findings are obtained when the MSCI ESG index is used (Table A.1).

The other diagnostic tests of residuals like 'normality', 'autocorrelation', 'heteroscedasticity', and 'ARCH effect' show favorable outcomes as we fail to reject the null hypotheses at a 5% level in each case. Model M2 (Table A.1) also does not indicate any violation of residual diagnostics. Thus, the overall diagnostics strengthen our model selection and implementation.

While examining the long-and short-run effects of ESG_NSE and the influence of control variables PUI and VIX on the sentiment index, we observe that positive changes in ESG_NSE have a weaker impact on SENT than its negative changes. Because ESG_NSE$^{(+)}$ is statistically significant at 10% level, but ESG_NSE$^{(-)}$ has statistical significance at 1% level. Directionally, the long-run effect of ESG_NSE has an opposite asymmetric influence on the SENT variable because negative (positive) movements in ESG_NSE have a positive (negative) effect on the sentiment index. As a control variable, VIX significantly affects investor sentiment more than PUI. Scrutiny of short-run effects of the ESG index shows that positive changes impact the SENT negatively with a one-month lag, whereas the negatives of ESG_NSE do not have any explicit impact on SENT. ΔVIX continues to be a more persistent influencer on SENT than ΔPUI, spanning the lag of five months. ESG_MSCI validates similar outcomes (Table A.1). The findings of models M3 and M4 with the ESG index as the dependent variable validate each other where the investor sentiment (SENT) does not have any impact on the ESG index.[10] VIX remains the dominant driver of the ESG index, both in the long and short-run over PUI. The outcomes corroborate the orthogonalization process to remove the muddling effect of macroeconomic fundamentals on investor sentiment, as PUI, which is a measure of macroeconomic performance (Baker et al., 2016), is insignificant in our results.

In summary, NARDL results suggest the variables under study share a long-term link (cointegration) which is asymmetric. We found that an increase(decrease) in the ESG index weakens (strengthens) investor sentiment. On the contrary, as against conventional wisdom, investor sentiment does not affect the ESG index.

4.4. QNARDL results

We now examine the possibility of distributional asymmetry across quantiles for ESG and SENT variables using Eq. (8) for models M1 to M4. The QNARDL estimation aids in evaluating the presence of skewness in the empirical findings of NARDL that only

[9] To maintain brevity, we have shown empirical results of ESG_NSE and SENT (models M1 and M3) in the main text. ESG_MSCI and SENT (M2 and M4) are used to validate the findings and hence kept in Appendix.

[10] For models M3 and M4, we have also deployed the ARDL bounds test to examine if over parametrization causes SENT not to impact the ESG index. We find that the ESG is not cointegrated with SENT when the former is a dependent variable. Results are not discussed here but are available with authors on request.

Table 5
Bounds testing for cointegration for NARDL models.

F-Statistics	Without trend		With trend	
M1. F(SENT/ESG_NSE$^{(+)}$, ESG_NSE$^{(-)}$, PUI, VIX)	45.306** (1, 2, 0, 0, 6)		43.562** (1, 2, 0, 0, 6)	
M2. F(SENT/ESG_MSCI$^{(+)}$, ESG_MSCI$^{(-)}$, PUI, VIX)	42.133** (1, 2, 0, 4, 6)		38.511**(1, 2, 0, 4, 6)	
M3. F(ESG_NSE/ SENT$^{(+)}$, SENT$^{(-)}$, PUI, VIX)	5.447** (1, 0, 0, 0, 1)		5.99** (1, 1, 0, 0, 1)	
M4. F(ESG_MSCI/ SENT$^{(+)}$, SENT$^{(-)}$, PUI, VIX)	4.00** (1, 0, 0, 1, 4)		4.371** (1, 0, 0, 0, 1)	
**F-critical at 5% level	I(0) 2.56	I(1) 3.49	I(0) 3.05	I(1) 3.97
***F-critical at 1% level	3.29	4.37	3.81	4.92

Note: () shows the lag order. The optimal lag order is decided based on Hannan Quinn information criterion.

Table 6
NARDL estimation results.

M1. f (SENT/ESG_NSE$^{(+)}$, ESG_NSE $^{(-)}$, PUI, VIX)		M3. f (ESG_NSE/ SENT$^{(+)}$, SENT $^{(-)}$, PUI, VIX)	
Intercept	0.719* (0.06)	*Intercept*	180.374*** (0.00)
$SENT_{t-1}$	−1.162*** (0.00)	ESG_NSE_{t-1}	−0.160*** (0.00)
$ESG\_NSE^{+}_{t-1}$	−0.001* (0.09)	$SENT^{+}_{t}$	−1.268 (0.80)
$ESG\_NSE^{-}_{t}$	−0.003*** (0.00)	$SENT^{-}_{t}$	−7.348 (0.18)
PUI_t	0.003 (0.24)	PUI_t	−0.088 (0.55)
VIX_{t-1}	−0.135*** (0.00)	VIX_{t-1}	−2.528** (0.05)
$\Delta ESG\_NSE^{+}_{t}$	0.001 (0.39)	ΔVIX_t	−9.382** (0.00)
$\Delta ESG\_NSE^{+}_{t-1}$	−0.007*** (0.00)		
ΔVIX_t	0.011 (0.49)		
ΔVIX_{t-1}	0.114*** (0.00)		
ΔVIX_{t-2}	0.099*** (0.00)		
ΔVIX_{t-3}	0.078*** (0.00)		
ΔVIX_{t-4}	0.049*** (0.00)		
ΔVIX_{t-5}	0.110*** (0.00)		
Diagnostics			
Adj. R^2	0.59	Adj. R^2	0.99
Long-run asymmetry (*p*-value)	20.290***(0.00)	Long-run asymmetry (*p*-value)	1.923 (0.16)
CUSUM	ST	CUSUM	ST
CUSUMSQ	UST	CUSUMSQ	UST
χ2 (Serial Correlation) (*p*-value)	1.131 (0.51)	χ2 (Serial Correlation) (*p*-value)	3.947 (0.14)
χ2 (Heteroscedasticity) (*p*-value)	12.955 (0.45)	χ2(Heteroscedasticity) (*p*-value)	8.977 (0.17)
JB (Normal) (*p*-value)	7.388 (0.06)	JB(Normal) (*p*-value)	0.539 (0.76)
ARCH (10) (*p*-value)	15.108 (0.12)	ARCH (10) (*p*-value)	13.639 (0.19)

Note: () represents p-values. '*,' '**' and '***' imply significance at 10%, 5%, and 1% level, respectively.

Table 7
Quantile NARDL estimation results with ESG_NSE.

NARDL – Quantile	M1. f (SENT/ESG_NSE$^{(+)}$, ESG_NSE $^{(-)}$, PUI, VIX)				M3. f (ESG_NSE/ SENT$^{(+)}$, SENT $^{(-)}$, PUI, VIX)	
	$ESG\_NSE_t^+$	$ESG\_NSE_{t-1}^+$	$ESG\_NSE_{t-2}^+$	$ESG\_NSE_t^-$	$SENT_t^+$	$SENT_t^-$
0.10	0.312 (0.76)	−1.189 (0.24)	1.438 (0.15)	−1.400 (0.16)	−0.270 (0.78)	−1.070 (0.29)
0.25	−0.354 (0.72)	−1.393 (0.17)	2.982*** (0.00)	−1.221 (0.22)	−0.462 (0.65)	−0.908 (0.37)
0.50	0.449 (0.65)	−4.602*** (0.00)	5.080*** (0.00)	−2.504** (0.01)	−0.384 (0.70)	−0.946 (0.35)
0.75	−0.710 (0.48)	−4.286*** (0.00)	6.243*** (0.00)	−3.372*** (0.00)	−0.028 (0.98)	0.301 (0.76)
0.90	0.025 (0.98)	−2.978*** (0.00)	3.972*** (0.00)	−1.837* (0.07)	0.074 (0.94)	−0.575 (0.57)

Notes: () represent p-values. *, ** and *** shows 10%, 5% and 1% significance level.

estimate the mean quantile. Table 7 shows the QNARDL result for models M1 and M3. The quantile estimation for control variables PUI and VIX are shown in Figs. 1 and 2. Results on distributional asymmetries across quantiles for ESG_MSCI and SENT (M2 and M4) are shown in the Appendix (Tables A.2 and A.3, Figs. A.3 and A.4). The five quantiles are selected based on the frequency distribution of ESG and SENT and to represent the best of the results in congruence with the NARDL results.

QNARDL estimation of the model M1 when SENT is the dependent variable shows that the speed of adjustment parameter is significantly negative mostly across lower quantiles (Fig. 1), indicating that the long-run relationship between variables is quantile dependent. The model M3 does not show a quantile-dependent long-run link between ESG_NSE and SENT (Fig. 2) as the $ESG\_NSE_{(t-1)}$ is not statistically significant. Results of M2 and M4 validate the above outcomes (Figs. A.3 and A.4). QNARDL results also support the inverse asymmetric impact of ESG_NSE over investor sentiment, where negative(positive) changes in ESG_NSE lead to positive(negative) results in investor sentiment (Fig. 1) for the short run. This can be observed in Table 7, where at higher quantiles of 50% and above, negative(/positive) changes in ESG for the period t (/t−1) leads to positive(/negative) changes in SENT. This means a decrease in ESG_NSE influences the sentiment positively, and the effect is visible only for higher quantiles. However, when the lagged period increases to two months, the impact on investor sentiment is positive. The negative effects of the ESG index on SENT are maximum at the 90th quantile, whereas positive influence attains a maximum at the 75th quantile. The results indicate the presence of extreme bias in the asymmetric long-run relationship between investor sentiment and the ESG index when the latter is the explanatory variable. The positive effects of the ESG index over SENT, in the long run, are also validated for the MSCI ESG index, model M2 (Table A.2).

Thus, in summary, the above outcomes indicate that a higher ESG index may encourage investor sentiment eventually, if not instantaneously. QNARDL results further validate our findings of the NARDL model, where the models M3 (Table 7) and M4 (Table A.2) demonstrate no clear evidence of investor sentiment index driving ESG ratings.[11] VIX is the persistent influencer across all quantiles in the long-and short-run outperforming PUI for both ESG indices and investor sentiment models (Figs. 2 and A.4).

As a measure of robustness, we perform the Wald test to examine the parameter constancy across quantiles for models M1 to M4.[12] Overall, the null of equality of slope coefficients is rejected for model M1, indicating that the parameter estimates differ across quantiles. The outcome justifies the employment of QNARDL. A similar finding is obtained when the MSCI ESG index is utilized. However, we fail to reject the null of parameter constancy when ESG is the dependent variable (models, M3 and M4). The outcomes are in line with the NARDL results suggesting that investor sentiment does not cause an ESG index. The Wald test of parameter constancy (Table A.4) is also rejected for the lagged dependent variable when the ESG_NSE index is used as the explanatory variable implying the heterogeneity of parameter estimates across five quantiles. It failed to reject the null of parameter constancy for the explanatory variables, possibly because the impact on the investor sentiment index 'SENT' is only observed in the higher quantiles.

Thus, our study is a catalyst for the sustainable investment preferences of investors in an emerging economy like India, where the poor performance of the ESG index stimulates investor sentiment. ESG index boosts investor sentiment in the long run. This implies that ESG initiatives might not attract positive sentiment immediately, but they do impact investors positively in the future. It indicates that the ESG index may be able to attract positive investor sentiment if the companies continue their sustainability quest. The absence of causality from SENT to ESG indicates that ESG norms are still not well integrated into the investment culture of the country and remain an imposition by policymakers. This implies that ESG factors are still absent in investor sentiment. In other words, the market activities of large corporates & investors do not reflect ESG aspects, hence sentiment index is unable to cause changes in the ESG index in the financial market. Overall, the findings signal investors' indifference towards ESG aspects in India, posing a serious breach in the purpose of ESG reporting and a dire need to revisit the ESG policies and approach.

Our study supports the findings of Dyck et al. (2019), who found that firms' environmental and social (E&S) performance in 45 developed and developing countries does not depend on institutional investors, especially in those countries where E&S norms are weak. The current work validates the findings of Khemir et al. (2019) that ESG influences investment decisions for the Indian market, where profit-oriented institutional investors hold the lion's share and is still in the development phase. Our findings on the dominant role of the ESG index in influencing investor sentiment index are unique and differ from earlier studies which advocated the power of investor sentiment in driving the financial markets (Haritha and Rishad, 2020; Khan et al., 2020;

11 We applied the QARDL model to recheck the distribution asymmetries across five quantiles for models M3 and M4. Although the speed of adjustment parameter is found to be statistically significant across all quantiles, the coefficients are greater than one and do not possess negative signs, indicating unstable relation. Results are not discussed here but can be produced upon request.

12 Results of M2 and M4 are available in Table A.4.

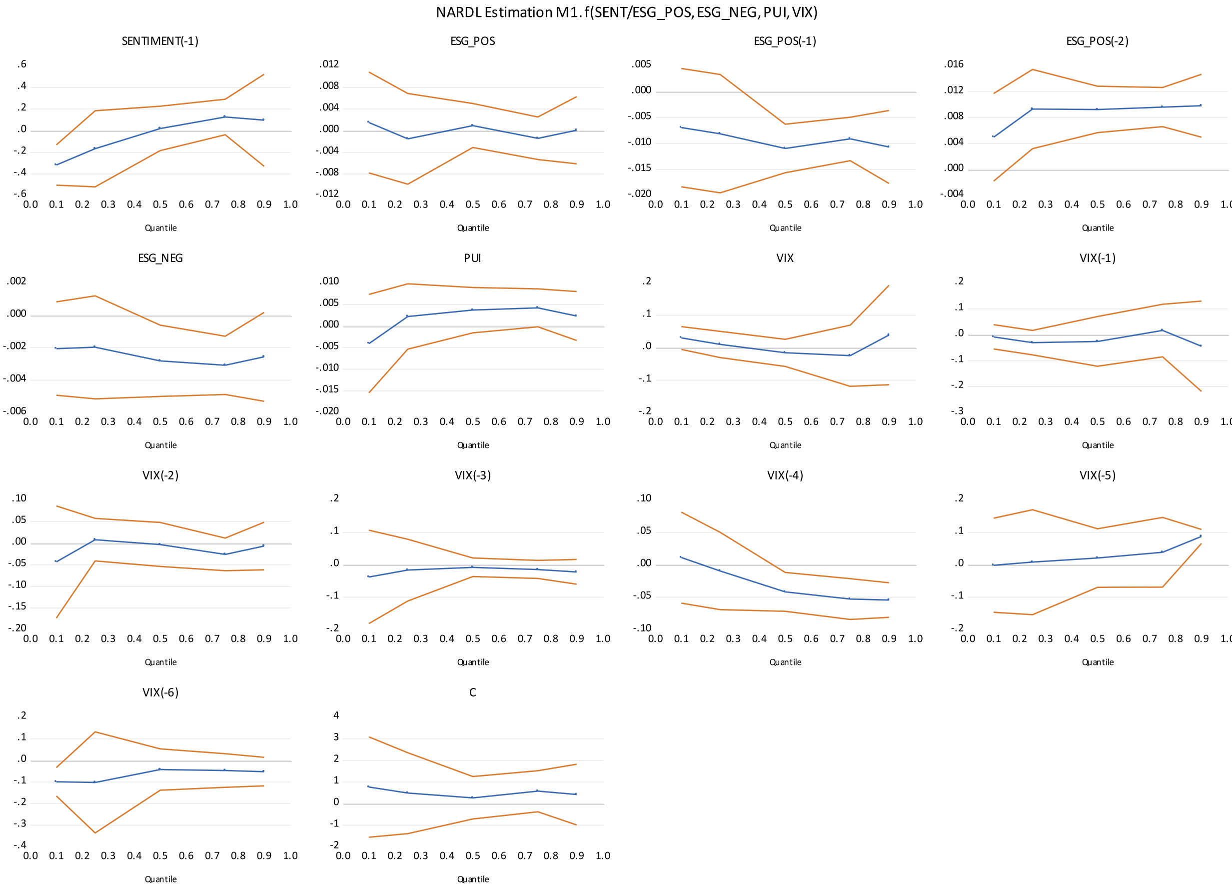

Fig. 1. QNARDL Estimation: M1. f (SENT/ESG_NSE$^{(+)}$, ESG_NSE$^{(-)}$, PUI, VIX).

Paramanik and Singhal, 2020; Piñeiro-chousa et al., 2021; Wang et al., 2021). The current work also contradicts previous studies (Chen and Yang, 2020; Ford et al., 2022; Vuong, 2022) which advocate the influence of investor sentiment on ESG scores for the firms located in Taiwan, the US, and Japan respectively. The dissimilarity in empirical outcomes may be attributed to the difference in data frequency, choice of variables, econometric methodologies applied, and geographic locations.

4.5. NARDL and QNARDL results: pre-COVID period

Since studies (Naeem et al., 2023; Umar et al., 2021; Umar and Gubareva, 2021) suggest an impact of the COVID pandemic on the ESG index, we also estimated NARDL and QNARDL models to examine the relationship between ESG index and investor sentiment index for the pre-COVID period (Apr 2011 to Feb 2020).[13] Results (Tables A.5–A.6) mostly remain similar in the pre-COVID period. The relationship is cointegrated which shows asymmetric and quantile dependency behavior like the entire study period. Higher ESG index continues to show a negative influence on investor sentiment. However, the coefficient weights are lesser in the pre-COVID period compared to the entire sample. VIX also shows similar findings. Thus, the pre-COVID era does not demonstrate any significant changes in the overall empirical outcomes of the study.

5. Conclusion

There has been an escalating demand for sustainable investment in the world over the last few years, and India is no exception in that context. ESG-compliant companies are increasing, giving promising returns, with the ESG index continuously growing steadily at the NSE and MSCI exchanges in India. With all these factors in play, the current study examines the dynamic nexus between the ESG index and investor sentiment in India, a domain of research that remains unexplored even for global economies. Our study used NARDL and QNARDL cointegration models to investigate the non-linear quantile-dependent asymmetric relationship between the ESG index and investor sentiment to capture the investors' behavior prevalent in the financial markets. Economic policy uncertainty and volatility index are used as control variables. We have also estimated NARDL and QNARDL models for the pre-COVID period.

We tested four NARDL and QNARDL models with NSE and MSCI ESG indices in a multivariate framework for India. We found cointegration in the link between the investor sentiment index and the ESG index, confirming the presence of a long-run asymmetric and quantile-dependent relationship in all models. Results demonstrate a one-way asymmetric quantile dependence between the ESG index and investor sentiment index when the latter is the dependent variable. Our study reveals that the

[13] We have not estimated NARDL and QNARDL models during COVID period due to the paucity of observations of monthly series. However, we have estimated MIDAS models for the entire sample as well as pre-and COVID subperiods where monthly investor sentiment index is regressed on daily data of ESG index. Findings suggest that VIX is the only statistically significant variable for investor sentiment for the three cases. This may be due to the linear assumptions of estimation in MIDAS model which cannot capture asymmetric and tail dependence non-linearity in the link between investor sentiment and ESG index. MIDAS results are available on request.

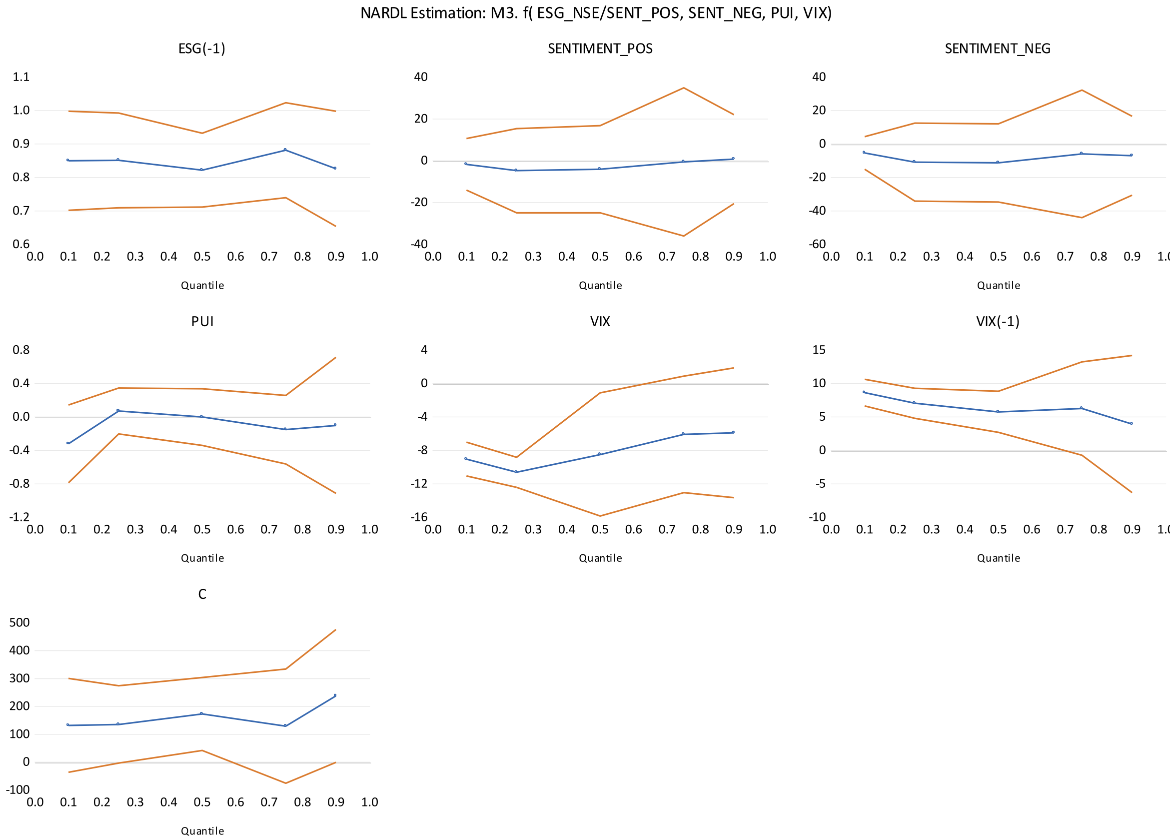

Fig. 2. NARDL Estimation: M3. f (ESG_NSE/ SENT$^{(+)}$, SENT $^{(-)}$, PUI, VIX).

rising ESG index, a plausible outcome of increasing ESG ratings of companies, weakens investor sentiment. On the other hand, investor sentiment plays no role in affecting the ESG index. The QNARDL model also supported these findings at higher quantiles, as a higher ESG index caused investor sentiment to decrease. Interestingly, the relationship reversed at higher lags where the ESG index starts influencing SENT positively. Results for the pre-COVID period do not show any significant differences. This implies that ESG initiatives might not attract positive sentiment immediately, but they do impact investors positively in the longer run. This puts in place the hope that the ESG index will be able to attract positive investor sentiment if the companies continue their sustainability quest. It also indicates that ESG efforts are at a vision state of companies and the country has a long way to go before the initiatives start reflecting in the market activities of firms and investors. India has 23 ESG funds compared to 500 or more in the U.S. and Britain, so it has a long way to go in sustainable investing (Murugaboopathy and Dogra, 2021). The findings of no causality flowing from investor sentiment to the ESG index signal that the investors are indifferent toward all the ESG initiatives being taken by the companies and continue to focus on the traditional monetary benefits of their investments. Thus, the current study contributes to the literature by unveiling the fact that ESG investing is still not well integrated into the Indian investor sentiment and is a far-flung task before it starts impacting the financial markets.

Our results carry insightful implications for policymakers in general and Indian ESG companies in particular. Although the focus on responsible investing in environmental, social, and governance has intensified in the last few years, its manifestation in Indian investor sentiment is still a long way. The importance of ESG ratings is still not well absorbed amongst investors who prefer to be oblivious in their actions towards responsible investing. While it is difficult to narrow down to a single reason behind the immutability of investor sentiment on the ESG index, short-term gains overpowering the investor's mood depending mainly on the market volatility play an obvious role. The market volatility fueling the investor sentiment and speculations further igniting the volatility is a spiral web net. In India, ESG ratings are a feel-good factor on companies' annual reports that boost auditors' confidence but have not earned investors' trust yet. Integration of ESG aspects in bolstering investor sentiment requires a cultural shift in investment which can pave the way for responsible investments in the future.

Pollution, climate change, violence, and hunger are some of the ongoing global challenges the world has been confronting. It is just the beginning, and the future is grim. Take it as a necessity or an obligation, but the uphill battle for sustainability is the only way forward. International organizations are continuously strategizing to promote sustainability in a better way, and qualitative corporate sustainability reporting (ESG) does create a collective social responsibility towards sustainability. After the COP26 Summit, several Indian companies, both from the private and public sectors, have laid out plans to reach net-zero carbon status. The subsequent COP27 promoted funds and technology transfer to nations in need, but also discussed the dark side of sustainability reporting, greenwashing. The results of this study pose a sour reality with hope for the future. The day investor sentiment will begin driving ESG, corporates will start receiving benefits for practicing sustainability and ESG practices will flourish. Till then, a continuous and sincere effort is needed from all the regulators and practitioners to keep the hope alive and carry the torch for sustainability. There is no doubt that Indian companies are engaged in ESG practices such as employee ownership, recyclability, education and supply chain sustainability, and regulators are continuously working to implement sustainability. But the incentive theory of motivation plays at both ends, and the investors of the corporates also need to feel incentivized to make an ESG investment. The regulators and facilitators of the financial markets need to implement measures to communicate the existence, accessibility, and importance of ESG information to investors. They also need to protect the investors from unethical ESG reporting practices such as greenwashing and standardizing the ESG accounting process. Future research can be directed to examine how ESG, and sentiment index nexus respond to the mediating effects of clean and dirty stocks.

CRediT authorship contribution statement

Samriddhi Dhasmana: Conceptualization, Data curation, Formal analysis, Writing – original draft, Software. **Sajal Ghosh:** Conceptualization, Formal analysis, Writing – review & editing, Supervision. **Kakali Kanjilal:** Conceptualization, Formal analysis, Software, Writing – review & editing, Supervision.

Acknowledgment

The authors are immensely grateful to the Editor and, four anonymous reviewers for their comprehensive review.

Appendix

See Figs. A.1–A.4 and Tables A.1–A.6.

Table A.1
NARDL estimation results.

M2. f (SENT/ESG_MSCI$^{(+)}$, ESG_MSCI$^{(-)}$, PUI, VIX)		M4. f (ESG_MSCI/SENT$^{(+)}$, SENT$^{(-)}$, PUI, VIX)	
Intercept	−0.481 (0.21)	*Intercept*	175.783 (0.00)
$SENT_{t-1}$	−1.144*** (0.00)	ESG_MSCI_{t-1}	−0.181*** (0.00)
$ESG\_MSCI^{+}_{t-1}$	−0.001 (0.16)	$SENT^{+}_{t}$	−3.249 (0.56)
$ESG\_MSCI^{-}_{t}$	−0.002*** (0.00)	$SENT^{-}_{t}$	−8.634 (0.15)
PUI_{t-1}	0.005* (0.09)	PUI_{t-1}	−0.098 (0.59)
VIX_{t-1}	−0.106*** (0.00)	VIX_{t-1}	−0.773 (0.66)
$\Delta ESG\_MSCI^{+}_{t}$	−0.002 (0.15)	ΔPUI_{t}	−0.452** (0.02)
$\Delta ESG\_MSCI^{+}_{t-1}$	−0.006*** (0.00)	ΔVIX_{t}	−8.823*** (0.00)
ΔPUI_{t}	−0.0004 (0.86)	ΔVIX_{t-1}	−0.280 (0.85)
ΔPUI_{t-1}	−0.00009 (0.97)	ΔVIX_{t-2}	−2.897** (0.03)
ΔPUI_{t-2}	−0.000005 (0.99)	ΔVIX_{t-3}	−3.259*** (0.00)
ΔPUI_{t-3}	0.007*** (0.00)		
ΔVIX_{t}	0.007 (0.65)		
ΔVIX_{t-1}	0.120*** (0.00)		
ΔVIX_{t-2}	0.080*** (0.00)		
ΔVIX_{t-3}	0.056*** (0.00)		
ΔVIX_{t-4}	0.035** (0.04)		
ΔVIX_{t-5}	0.110*** (0.00)		
Diagnostics			
Adj. R^2	0.60	Adj. R^2	0.98
Long-run asymmetry (*p*-value)	9.272***(0.00)	Long-run asymmetry (*p*-value)	1.923 (0.17)
CUSUM	ST	CUSUM	ST
CUSUMSQ	UST	CUSUMSQ	ST
χ2(Serial Correlation) (*p*-value)	2.815 (0.24)	χ2(Serial Correlation) (*p*-value)	4.083 (0.13)
χ2(Heteroscedasticity) (*p*-value)	18.751(0.34)	χ2(Heteroscedasticity) (*p*-value)	14.570 (0.15)
JB(Normal) (*p*-value)	1.768 (0.41)	JB(Normal) (*p*-value)	7.596 (0.02)**
ARCH (10) (*p*-value)	6.160 (0.80)	ARCH (10) (*p*-value)	3.905 (0.95)

Note: () represents p-values. '*,' '**' and '***' imply significance at 10%, 5%, and 1% level, respectively.

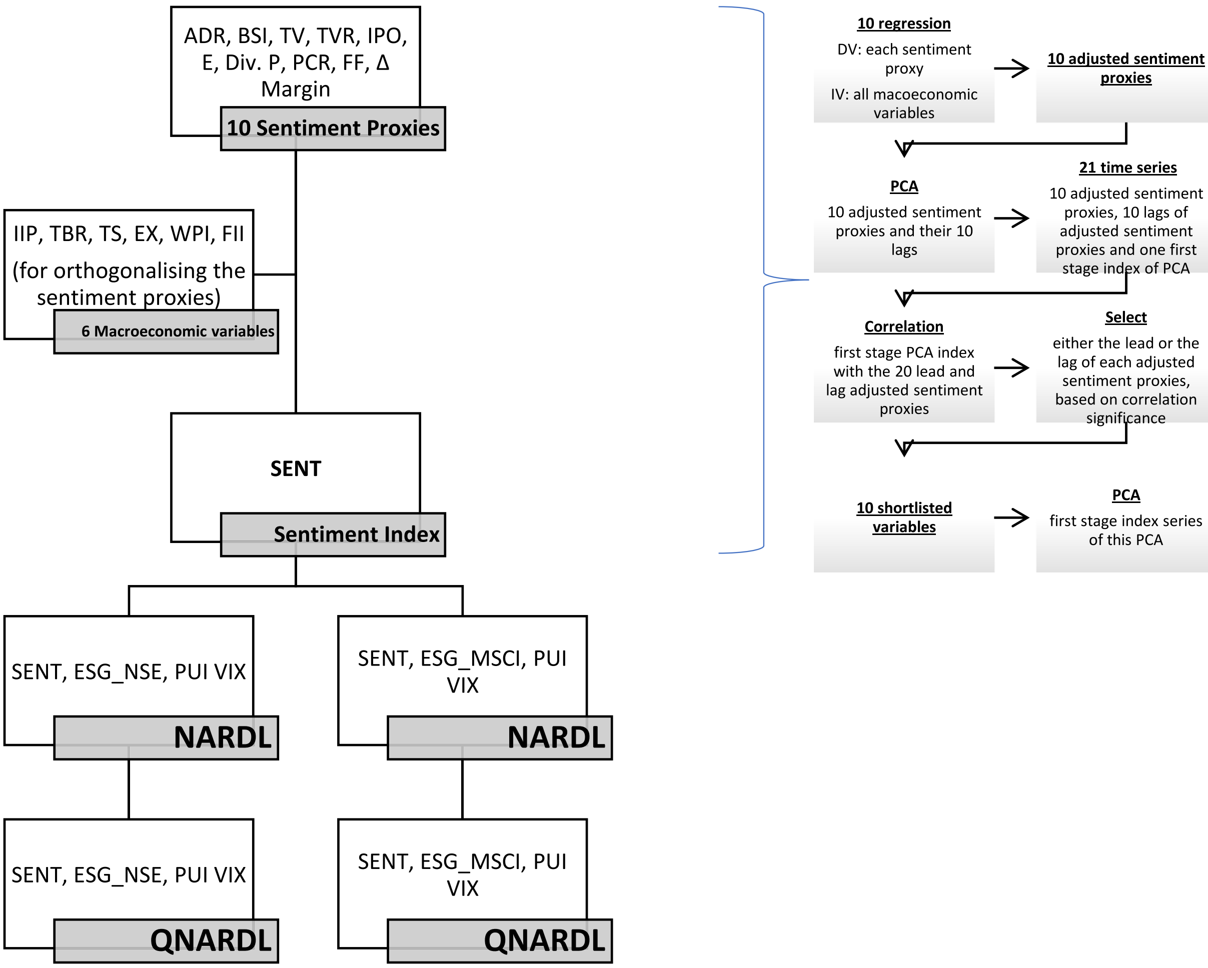

Fig. A.1. A summary snapshot of modeling strategy.

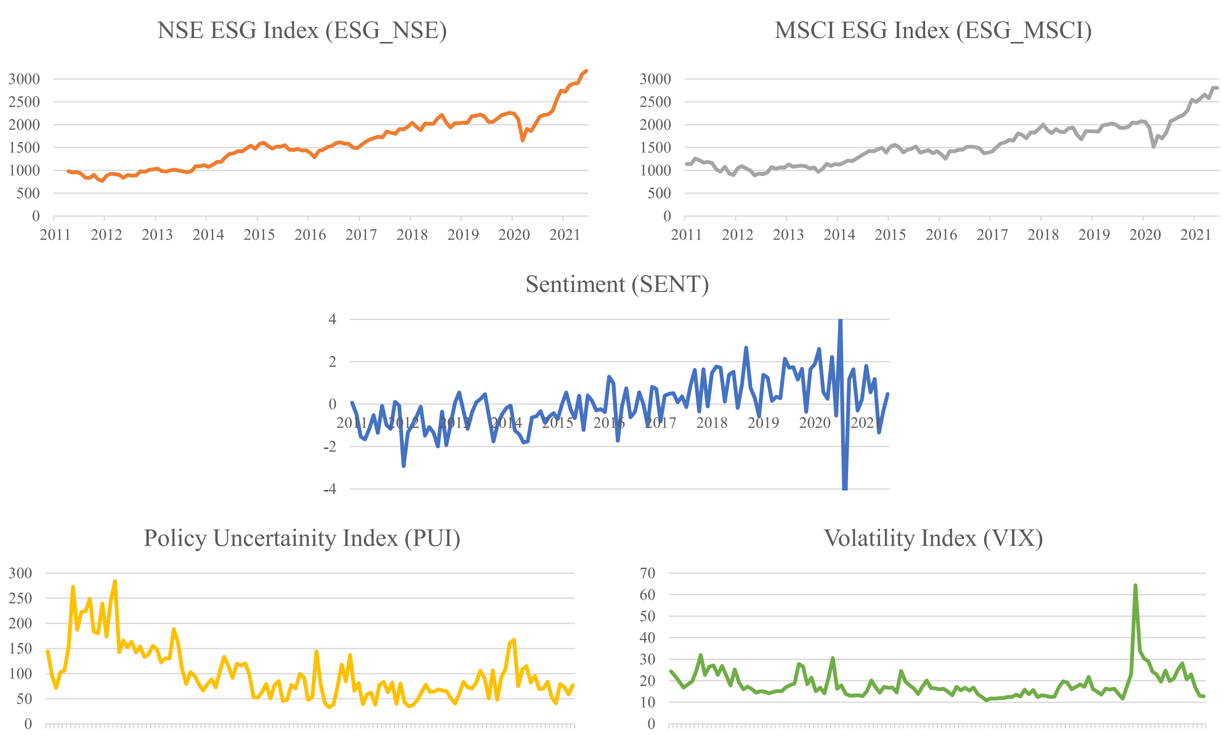

Fig. A.2. Line graphs of the time-series variables employed in the study.

Table A.2
Quantile NARDL estimation results with ESG_MSCI.

NARDL – Quantile	M2. f (SENT/ESG_MSCI$^{(+)}$, ESG_MSCI $^{(-)}$, PUI, VIX)				M4. f (ESG_MSCI/ SENT$^{(+)}$, SENT $^{(-)}$, PUI, VIX)	
	$ESG\_MSCI_t^+$	$ESG\_MSCI_{t-1}^+$	$ESG\_MSCI_{t-2}^+$	$ESG\_MSCI_t^-$	$SENT_t^+$	$SENT_t^-$
0.10	−0.805 (0.42)	0.143 (0.89)	1.354 (0.18)	−0.665 (0.51)	−0.542 (0.59)	−1.129 (0.26)
0.25	−1.031 (0.31)	−0.965 (0.34)	2.237** (0.03)	−0.562 (0.58)	−0.023 (0.98)	−0.732 (0.47)
0.50	−1.673* (0.09)	−2.427** (0.02)	4.815*** (0.00)	−1.051 (0.30)	0.088 (0.93)	−0.337 (0.74)
0.75	−0.651 (0.52)	−2.453** (0.02)	5.163*** (0.00)	−1.215 (0.23)	−0.757 (0.45)	−1.018 (0.31)
0.90	−0.934 (0.35)	−0.929 (0.35)	1.553 (0.12)	−0.656 (0.51)	−1.600 (0.11)	−1.979 (0.05)

Notes: () represent p-values. *, ** and *** shows 10%, 5% and 1% significance level.

Table A.3
Wald test for parameter constancy between quantiles with ESG_NSE.

M1. f (SENT/ESG_NSE$^{(+)}$, ESG_NSE $^{(-)}$, PUI, VIX)		M3. f (ESG_NSE/ SENT$^{(+)}$, SENT $^{(-)}$, PUI, VIX)	
Intercept	0.376 (0.83)	*Intercept*	0.922 (0.63)
$SENT_{t-1}$	14.660*** (0.00)	ESG_NSE_{t-1}	1.349 (0.85)
$ESG\_NSE_t^+$	2.487 (0.64)	$SENT_t^+$	0.221 (0.99)
$ESG\_NSE_{t-1}^+$	1.468 (0.83)	$SENT_t^-$	0.469 (0.97)
$ESG\_NSE_{t-2}^+$	2.257 (0.69)	PUI_t	5.016 (0.29)
$ESG\_NSE_t^-$	0.736 (0.95)	VIX_t	4.753 (0.31)
PUI_t	2.314 (0.68)	VIX_{t-1}	3.999 (0.41)
ΔVIX_t	4.291 (0.37)		
ΔVIX_{t-1}	2.377 (0.67)		
ΔVIX_{t-2}	2.837 (0.59)		
ΔVIX_{t-3}	0.630 (0.96)		
ΔVIX_{t-4}	3.523 (0.47)		
ΔVIX_{t-5}	2.917 (0.57)		
ΔVIX_{t-6}	1.683 (0.79)		
Diagnostics			
Wald Test (Equality of slope) (*p*-value)	101.536***(0.00)	Wald Test (Equality of slope) (*p*-value)	27.039 (0.630)
Box–Ljung Q-Stat (10) (*p*-value)	4.664 (0.91)	Box–Ljung Q-Stat (10) (*p*-value)	11.412 (0.32)
JB(Normal) (*p*-value)	10.657*** (0.00)	JB(Normal) (*p*-value)	0.439 (0.80)
ARCH (10) (*p*-value)	5.173 (0.87)	ARCH (10) (*p*-value)	12.077 (0.28)

Note: () represents p-values. ‘*,’ ‘**’ and ‘***’ imply significance at 10%, 5%, and 1% level, respectively.

Table A.4
Wald test for parameter constancy with ESG_MSCI.

M2. f (SENT/ESG_MSCI$^{(+)}$, ESG_MSCI $^{(-)}$, PUI, VIX)		M4. f (ESG_MSCI/ SENT$^{(+)}$, SENT $^{(-)}$, PUI, VIX)	
Intercept	2.280 (0.32)	*Intercept*	0.492 (0.78)
$SENT_{t-1}$	2.113 (0.72)	ESG_MSCI_{t-1}	2.283 (0.68)
$ESG\_MSCI_t^+$	0.327 (0.99)	$SENT_t^+$	1.922 (0.75)
$ESG\_MSCI_{t-1}^+$	1.710 (0.79)	$SENT_t^-$	1.563 (0.82)
$ESG\_MSCI_{t-2}^+$	2.989 (0.56)	PUI_t	3.958 (0.41)
$ESG\_MSCI_t^-$	0.082 (0.99)	PUI_{t-1}	3.319 (0.51)
PUI_t	2.568 (0.63)	VIX_t	2.465 (0.65)
PUI_{t-1}	1.661 (0.80)	VIX_{t-1}	0.552 (0.97)
PUI_{t-2}	2.163 (0.71)	VIX_{t-2}	1.701 (0.79)
PUI_{t-3}	3.933 (0.42)	VIX_{t-3}	3.075 (0.55)
PUI_{t-4}	1.142 (0.89)	VIX_{t-4}	3.281 (0.51)
ΔVIX_t	0.643 (0.96)		
ΔVIX_{t-1}	1.558 (0.82)		
ΔVIX_{t-2}	0.319 (0.99)		
ΔVIX_{t-3}	0.637 (0.96)		
ΔVIX_{t-4}	3.223 (0.52)		
ΔVIX_{t-5}	2.980 (0.56)		
ΔVIX_{t-6}	1.802 (0.77)		
Diagnostics			
Wald Test (Equality of slope) (p-value)	88.974** (0.04)	Wald Test (Equality of slope) (p-value)	41.188 (0.41)
Box–Ljung Q-Stat (10) (p-value)	4.657 (0.91)	Box–Ljung Q-Stat (10) (p-value)	4.664 (0.91)
JB(Normal) (p-value)	209.841*** (0.00)	JB(Normal) (p-value)	10.657*** (0.00)
ARCH (10) (p-value)	33.295 (0.18)	ARCH (10) (p-value)	5.173 (0.88)

Note: () represents p-values. '*,' '**' and '***' imply significance at 10%, 5%, and 1% level, respectively.

Table A.5
NARDL estimation results: pre-COVID.

M1. f (SENT/ESG_NSE$^{(+)}$, ESG_NSE $^{(-)}$, PUI, VIX)		M3. f (ESG_NSE/ SENT$^{(+)}$, SENT $^{(-)}$, PUI, VIX)	
Intercept	−0.779* (0.08)	*Intercept*	180.765*** (0.00)
$SENT_{t-1}$	−1.021*** (0.00)	ESG_NSE_{t-1}	−0.143*** (0.00)
$ESG\_NSE^{+}_{t-1}$	−0.0003 (0.50)	$SENT^{+}_{t-1}$	8.795 (0.25)
$ESG\_NSE^{-}_{t}$	−0.001** (0.05)	$SENT^{-}_{t}$	4.592 (0.58)
PUI_t	0.002 (0.22)	PUI_t	−0.153 (0.28)
VIX_{t-1}	−0.044** (0.04)	VIX_{t-1}	−1.436 (0.40)
$\Delta ESG\_NSE^{+}_{t}$	0.001 (0.40)	ΔVIX_t	−7.027*** (0.00)
$\Delta ESG\_NSE^{+}_{t-1}$	−0.008*** (0.00)		
$\Delta ESG\_NSE^{-}_{t}$	−0.005** (0.03)		
$\Delta ESG\_NSE^{-}_{t-1}$	−0.006** (0.00)		
ΔVIX_t	0.005 (0.78)		
ΔVIX_{t-1}	0.053** (0.00)		
ΔPUI_t	−0.002 (0.29)		
Diagnostics			
F-Stat (ARDL Bounds Test)	30.338***	F-Stat (ARDL Bounds Test)	2.910
F-Stat (NARDL Bounds Test)	28.931***	F-Stat (NARDL Bounds Test)	4.237**
Adj. R^2	0.74	Adj. R^2	0.99
Long-run asymmetry (*p*-value)	22.436***(0.00)	Long-run asymmetry (*p*-value)	2.346 (0.11)
CUSUM	ST	CUSUM	ST
CUSUMSQ	ST	CUSUMSQ	ST
χ2(Serial Correlation) (*p*-value)	0.355 (0.84)	χ2(Serial Correlation) (*p*-value)	2.263 (0.32)
χ2(Heteroscedasticity) (*p*-value)	11.040 (0.53)	χ2(Heteroscedasticity) (*p*-value)	10.701 (0.15)
JB(Normal) (*p*-value)	1.907 (0.38)	JB(Normal) (*p*-value)	1.666 (0.43)
ARCH (10) (*p*-value)	7.849 (0.64)	ARCH (10) (*p*-value)	3.224 (0.98)

Notes: () represents p-values. '*,' '**' and '***' imply significance at 10%, 5%, and 1% level, respectively. For ARDL, lower bounds and upper bounds critical values are 2.92 and 3.838 respectively. For NARDL, lower and upper bounds critical values are 2.688 and 3.698 respectively.

Table A.6
Quantile NARDL estimation results with ESG_NSE: pre-COVID.

NARDL – Quantile	M1. f (SENT/ESG_NSE$^{(+)}$, ESG_NSE $^{(-)}$, PUI, VIX)						M3. f (ESG_NSE/ SENT$^{(+)}$, SENT $^{(-)}$, PUI, VIX)	
	$ESG\_NSE^{+}_{t}$	$ESG\_NSE^{+}_{t-1}$	$ESG\_NSE^{+}_{t-2}$	$ESG\_NSE^{-}_{t}$	$ESG\_NSE^{-}_{t-1}$	$ESG\_NSE^{-}_{t-2}$	$SENT^{+}_{t}$	$SENT^{-}_{t}$
0.10	0.001 (0.75)	−0.005 (0.31)	0.004 (0.25)	−0.006 (0.13)	−0.005 (0.26)	0.009*** (0.00)	−0.187 (0.23)	−2.386 (0.16)
0.25	0.0009 (0.75)	−0.008* (0.06)	0.008*** (0.01)	−0.003 (0.19)	−0.006 (0.15)	0.008*** (0.00)	−0.149 (0.19)	−2.145 (0.11)
0.50	0.001 (0.66)	−0.010*** (0.00)	0.009*** (0.00)	−0.005* (0.10)	−0.002 (0.62)	0.006** (0.02)	4.348 (0.68)	−1.600 (0.89)
0.75	0.001 (0.60)	−0.011** (0.00)	0.010*** (0.00)	−0.006* (0.09)	−0.004 (0.51)	0.002 (0.51)	6.479 (0.65)	2.667 (0.86)
0.90	0.002 (0.39)	−0.008** (0.04)	0.006*** (0.06)	−0.004 (0.17)	−0.0001 (0.96)	0.003 (0.23)	10.285 (0.33)	5.689 (0.64)

Notes: () represent p-values. *, ** and *** shows 10%, 5% and 1% significance level. The parameter constancy test for $ESG\_NSE^{-}_{t-2}$ is statistically significant at 10% level of significance for the quantile (0.5 , 0.75) [0.004* (0.08)].

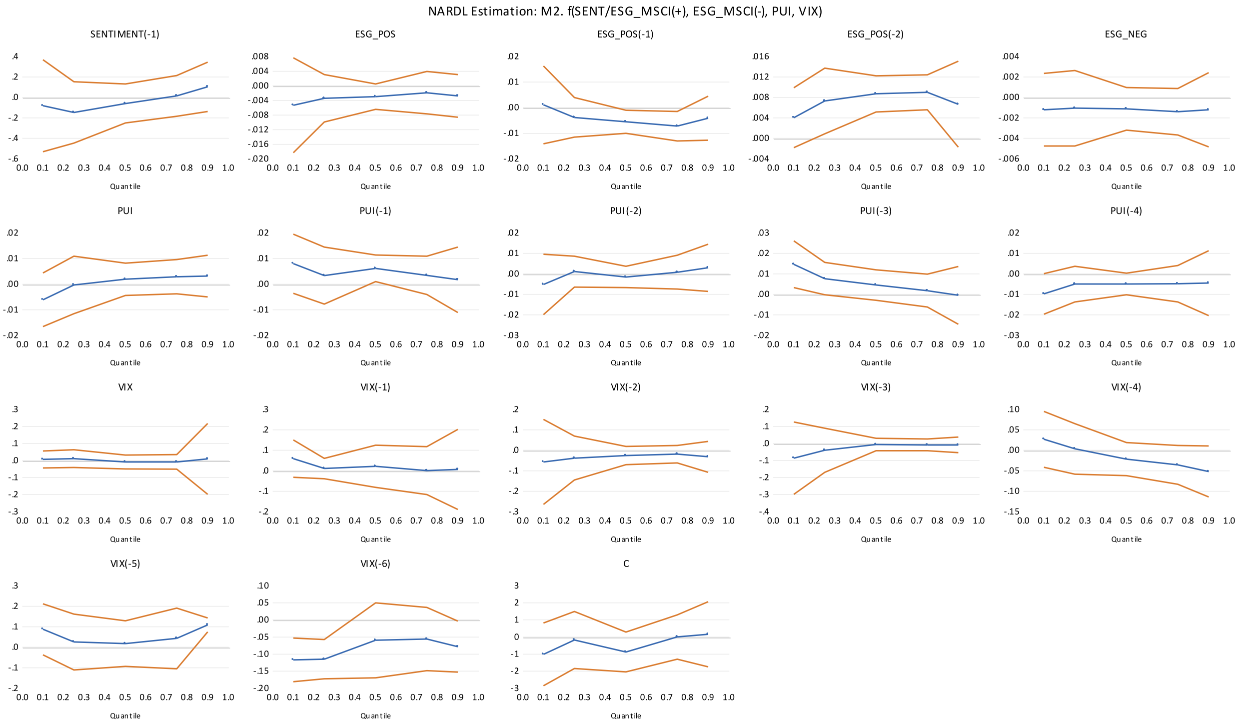

Fig. A.3. NARDL Estimation: M2. f(SENT/ESG_MSCI$^{(+)}$, ESG_MSCI$^{(-)}$, PUI, VIX).

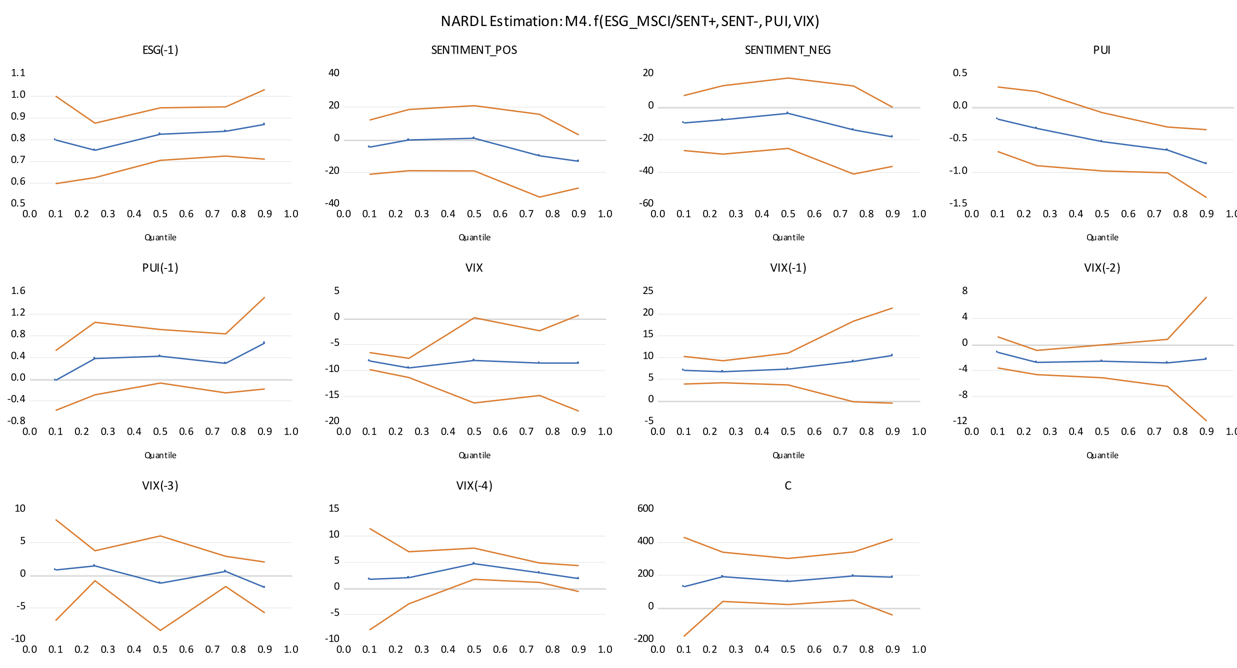

Fig. A.4. NARDL Estimation: M4. f(ESG_MSCI/SENT$^{(+)}$, SENT$^{(-)}$, PUI, VIX).

References

Al-Khazali, O., Bouri, E., Roubaud, D., 2018. The impact of positive and negative macroeconomic news surprises: Gold versus Bitcoin. Econ. Bull. 38, 373–382.

Alamoodi, A.H., Zaidan, B.B., Al-Masawa, M., Taresh, S.M., Noman, S., Ahmaro, I.Y.Y., Garfan, S., Chen, J., Ahmed, M.A., Zaidan, A.A., Albahri, O.S., Aickelin, U., Thamir, N.N., Fadhil, J.A., Salahaldin, A., 2021. Multi-perspectives systematic review on the applications of sentiment analysis for vaccine hesitancy. Comput. Biol. Med. 139, 104957. http://dx.doi.org/10.1016/j.compbiomed.2021.104957.

Andersson, E., Hoque, M., Rahman, M.L., Uddin, G.S., Jayasekera, R., 2020. ESG investment: What do we learn from its interaction with stock, currency and commodity markets? Int. J. Financ. Econ. 1–17. http://dx.doi.org/10.1002/ijfe.2341.

Baker, S.R., Bloom, N., Davis, S.J., 2022. India monthly [WWW Document]. Econ. Policy Uncertain. URL https://www.policyuncertainty.com/india_monthly.html, (accessed 4.21.22).

Baker, S.R., Bloom, N., Davis, S.J., Dashkeyev, V., Deriy, O., Dinh, E., Ezure, Y., Gong, R., Jindal, S., Kim, R., Klosin, S., Koh, J., Lajewski, P., Sachs, R., Shibata, I., Stephenson, C., Takeda, N., 2016. Measuring economic policy uncertainlty. Q. J. Econ. 131, 1593–1636. http://dx.doi.org/10.1093/qje/qjw024.Advance.

Baker, M., Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. J. Finance 61, 1645–1680. http://dx.doi.org/10.1111/j.1540-6261.2006.00885.x.

Baker, M., Wurgler, J., 2007. Investor sentiment in the stock market. J. Econ. Perspect. 21, 129–151. http://dx.doi.org/10.1257/jep.21.2.129.

Baker, M., Wurgler, J., Yuan, Y., 2012. Global, local, and contagious investor sentiment $. J. Financ. Econ. 104, 272–287. http://dx.doi.org/10.1016/j.jfineco.2011.11.002.

Bathia, D., Bredin, D., 2018. Investor sentiment: Does it augment the performance of asset pricing models? Int. Rev. Financ. Anal. 59, 290–303. http://dx.doi.org/10.1016/j.irfa.2018.03.014.

Bennani, H., 2020. Central bank communication in the media and investor sentiment. J. Econ. Behav. Organ. 176, 431–444. http://dx.doi.org/10.1016/j.jebo.2020.05.022.

Brown, Gregory W., Cliff, M.T., 2004. Investor sentiment and the near-term stock market. J. Empir. Financ. 11, 1–27. http://dx.doi.org/10.1016/j.jempfin.2002.12.001.

Buchheim, L., Dovern, J., Krolage, C., Link, S., 2022. Sentiment and firm behavior during the COVID-19 pandemic. J. Econ. Behav. Organ. 195, 186–198. http://dx.doi.org/10.1016/j.jebo.2022.01.011.

Chalkiadakis, I., Zaremba, A., Peters, G.W., Chantler, M.J., 2022. On-chain analytics for sentiment-driven statistical causality in cryptocurrencies. Blockchain Res. Appl. 3, 100063. http://dx.doi.org/10.1016/j.bcra.2022.100063.

Chang, Y.-C., Shao, R., Wang, N., 2022. Can stock message board sentiment predict future returns? Local versus nonlocal posts. J. Behav. Exp. Financ. 34, 100625. http://dx.doi.org/10.1016/j.jbef.2022.100625.

Chen, R., Bao, W., Jin, C., 2021. Investor sentiment and predictability for volatility on energy futures markets: Evidence from China. Int. Rev. Econ. Financ. 75, 112–129. http://dx.doi.org/10.1016/j.iref.2021.02.002.

Chen, Y., Lin, B., 2022. Quantifying the extreme spillovers on worldwide ESG leaders ' equity. Int. Rev. Financ. Anal. 84, 102425. http://dx.doi.org/10.1016/j.irfa.2022.102425.

Chen, Z., Xie, G., 2022. ESG disclosure and financial performance: Moderating role of ESG investors. Int. Rev. Financ. Anal. 83, 102291. http://dx.doi.org/10.1016/J.IRFA.2022.102291.

Chen, H., Yang, S.S., 2020. Do investors exaggerate corporate ESG information? Evidence of the ESG momentum effect in the Taiwanese market. Pacific-Basin Financ. J. 63, 101407. http://dx.doi.org/10.1016/j.pacfin.2020.101407.

Cheong, C.W.H., Sinnakkannu, J., Ramasamy, S., 2017. Reactive or proactive? Investor sentiment as a driver of corporate social responsibility. Res. Int. Bus. Financ. 42, 572–582. http://dx.doi.org/10.1016/j.ribaf.2017.07.002.

Cho, J.S., Kim, T., Shin, Y., 2015. Quantile cointegration in the autoregressive distributed-lag modeling framework. J. Econ. 188, 281–300. http://dx.doi.org/10.1016/j.jeconom.2015.05.003.

Citterio, A., King, T., 2023. The role of environmental, social, and governance (ESG) in predicting bank financial distress. Financ. Res. Lett. 51, 103411. http://dx.doi.org/10.1016/j.frl.2022.103411.

Daugaard, D., 2020. Emerging new themes in environmental, social and governance investing: a systematic literature review. Account. Financ. 60, 1501–1530. http://dx.doi.org/10.1111/acfi.12479.

de la Fuente, G., Ortiz, M., Velasco, P., 2021. The value of a firm's engagement in ESG practices: Are we looking at the right side? Long Range Plann http://dx.doi.org/10.1016/j.lrp.2021.102143.

De Long, J.B., Shleifer, A., Summers, L.H., Waldmann, R.J., 1990. Noise trader risk in financial markets. J. Polit. Econ. 98, 703–738.

De Spiegeleer, J., Höcht, S., Jakubowski, D., Reyners, S., Schoutens, W., 2021. ESG: a new dimension in portfolio allocation. J. Sustain. Financ. Invest. 1–41. http://dx.doi.org/10.1080/20430795.2021.1923336.

Díaz, V., Ibrushi, D., Zhao, J., 2021. Reconsidering systematic factors during the Covid-19 pandemic – the rising importance of ESG. Financ. Res. Lett. 38, 101870. http://dx.doi.org/10.1016/j.frl.2020.101870.

Dyck, A., Lins, K.V., Roth, L., Wagner, H.F., 2019. Do institutional investors drive corporate social responsibility? International evidence R. J. Financ. Econ. 131, 693–714. http://dx.doi.org/10.1016/j.jfineco.2018.08.013.

Economou, F., 2016. Herd behavior in frontier markets: Evidence from Nigeria and Morocco. In: Andrikopoulos, P., Gregoriou, G.N., Kallinterakis, V. (Eds.), Handbook of Frontier Markets. Academic Press, pp. 55–69. http://dx.doi.org/10.1016/B978-0-12-803776-8.00004-5.

Eliwa, Y., Aboud, A., Saleh, A., 2021. ESG practices and the cost of debt: Evidence from EU countries. Crit. Perspect. Account. 79, 102097. http://dx.doi.org/10.1016/j.cpa.2019.102097.

Engle, R.F., Granger, C.W.J., 1987. Co-integration and error correction: Representation, estimation, and testing. Econometrica 55, 251–276. http://dx.doi.org/10.2307/1913236.

Fatemi, A., Glaum, M., Kaiser, S., 2018. ESG performance and firm value: The moderating role of disclosure. Glob. Financ. J. 38, 45–64. http://dx.doi.org/10.1016/j.gfj.2017.03.001.

Fisher, K.L., Statman, M., 2000. Investor sentiment and stock returns. Financ. Anal. J. 56, 16–23. http://dx.doi.org/10.2469/faj.v56.n2.2340.

Fisher, K.L., Statman, M., 2003. Consumer confidence and stock returns. J. Portf. Manag. 30, 115–127. http://dx.doi.org/10.3905/jpm.2003.319925.

Ford, J.M., Gehricke, S.A., Zhang, J.E., 2022. Option traders are concerned about climate risks: ESG ratings and short-term sentiment. J. Behav. Exp. Finance 35, 100687. http://dx.doi.org/10.1016/j.jbef.2022.100687.

Ganganwar, V., Rajalakshmi, R., 2019. Implicit aspect extraction for sentiment analysis: A survey of recent approaches. Proc. Comput. Sci. 165, 485–491. http://dx.doi.org/10.1016/j.procs.2020.01.010.

Gao, Y., Li, Y., Zhao, C., Wang, Y., 2022. Risk spillover analysis across worldwide ESG stock markets: New evidence from the frequency-domain. North Am. J. Econ. Financ. 59, 101619. http://dx.doi.org/10.1016/j.najef.2021.101619.

Giudice, A. Del, Rigamonti, S., 2020. Does audit improve the quality of ESG scores? Evidence from corporate misconduct. Sustainability 12, 5670.

Gric, Z., Ehrenbergerova, D., Hodula, M., 2022. The power of sentiment: Irrational beliefs of households and consumer loan dynamics. J. Financ. Stab. 59, 100973. http://dx.doi.org/10.1016/j.jfs.2022.100973.

Haritha, P.H., Rishad, A., 2020. An empirical examination of investor sentiment and stock market volatility: evidence from India. Financ. Innov. 6, 34. http://dx.doi.org/10.1186/s40854-020-00198-x.

He, Z., 2020. Dynamic impacts of crude oil price on Chinese investor sentiment: Nonlinear causality and time-varying effect. Int. Rev. Econ. Financ 66, 131–153. http://dx.doi.org/10.1016/j.iref.2019.11.004.

Hkiri, B., Hammoudeh, S., Aloui, C., Shahbaz, M., 2018. The interconnections between U.S. financial CDS spreads and control variables: New evidence using partial and multivariate wavelet coherences. Int. Rev. Econ. Financ. 57, 237–257. http://dx.doi.org/10.1016/j.iref.2018.01.011.

IISL, 2018. IISL launches NIFTY ESG indices. Natl. Stock Exch..

India VIX Index*, 2021. [WWW Document].

Islam, M.A., 2021. Investor sentiment in the equity market and investments in corporate-bond funds. Int. Rev. Financ. Anal. 78, 101898. http://dx.doi.org/10.1016/j.irfa.2021.101898.

Johansen, S., Juselius, K., 1990. Maximum likelihood estimation and inference on cointegration—with appucations to the demand for money. Oxf. Bull. Econ. Stat. 52, 169–210.

Kanas, A., 2012. Modelling the risk-return relation for the S & P 100: The role of VIX. Econ. Model. 29, 795–809. http://dx.doi.org/10.1016/j.econmod.2011.10.010.

Khan, M.A., 2022. ESG disclosure and firm performance: A bibliometric and meta analysis. Res. Int. Bus. Financ. 61, 101668. http://dx.doi.org/10.1016/J.RIBAF.2022.101668.

Khan, M.A., Hernandez, J.A., Shahzad, S.J.H., 2020. Time and frequency relationship between household investors' sentiment index and US industry stock returns. Financ. Res. Lett. 36, 101318. http://dx.doi.org/10.1016/j.frl.2019.101318.

Khemir, S., Baccouche, C., Ayadi, S.D., 2019. The influence of ESG information on investment allocation decisions: An experimental study in an emerging country. J. Appl. Account. Res. 20, 458–480. http://dx.doi.org/10.1108/JAAR-12-2017-0141.

Kilic, Y., Akif, M., Ismail, E., Fatih, M., 2022. Return and risk spillovers between the ESG global index and stock markets: Evidence from time and frequency analysis. Borsa Istanbul Rev. http://dx.doi.org/10.1016/j.bir.2022.11.015.

Kim, J. (Jeanne), Dong, H., Choi, J., Chang, S.R., 2022. Sentiment change and negative herding: Evidence from microblogging and news. J. Bus. Res. 142, 364–376. http://dx.doi.org/10.1016/j.jbusres.2021.12.055.

Kumari, J., 2019. Investor sentiment and stock market liquidity: Evidence from an emerging economy. J. Behav. Exp. Financ. 23, 166–180. http://dx.doi.org/10.1016/j.jbef.2019.07.002.

Kumari, J., Mahakud, J., 2015. Does investor sentiment predict the asset volatility? Evidence from emerging stock market India. J. Behav. Exp. Financ. 8, 25–39. http://dx.doi.org/10.1016/j.jbef.2015.10.001.

Kumari, J., Mahakud, J., 2016. Investor sentiment and stock market volatility: Evidence from India. J. Asia-Pacific Bus. 17, 173–202. http://dx.doi.org/10.1080/10599231.2016.1166024.

Le, T.H., Luong, A.T., 2022. Dynamic spillovers between oil price, stock market, and investor sentiment: Evidence from the United States and Vietnam. Resour. Policy 78, 102931. http://dx.doi.org/10.1016/j.resourpol.2022.102931.

Lee, W.Y., Jiang, C.X., Indro, D.C., 2002. Stock market volatility, excess returns, and the role of investor sentiment. J. Bank. Financ. 26, 2277–2299. http://dx.doi.org/10.1016/S0378-4266(01)00202-3.

Li, H., Zhang, X., Zhao, Y., 2022. ESG and firm's default risk. Finance Res. Lett. 102713. http://dx.doi.org/10.1016/j.frl.2022.102713.

Long, W., Zhao, M., Tang, Y., 2021. International review of financial analysis can the Chinese volatility index reflect investor sentiment? Int. Rev. Financ. Anal. 73, 101612. http://dx.doi.org/10.1016/j.irfa.2020.101612.

Methodology Document for Equity Indices, 2022.

Mokni, K., Bouteska, A., Nakhli, M.S., 2022. Investor sentiment and Bitcoin relationship: A quantile-based analysis. North Am. J. Econ. Financ. 60, 101657. http://dx.doi.org/10.1016/j.najef.2022.101657.

MSCI ESG Ratings Methodology, 2020.

MSCI Index Calculation Methodology, 2012.

Murugaboopathy, P., Dogra, G., 2021. India has fewer ESG funds than other top 10 economies [WWW Document]. Reuters URL https://www.reuters.com/business/sustainable-business/india-has-fewer-esg-funds-than-other-top-10-economies-2021-08-26/.

Naeem, M.A., Mbarki, I., Shahzad, S.J.H., 2021. Predictive role of online investor sentiment for cryptocurrency market: Evidence from happiness and fears. Int. Rev. Econ. Financ. 73, 496–514. http://dx.doi.org/10.1016/j.iref.2021.01.008.
Naeem, M.A., Yousaf, I., Karim, S., Tiwari, A.K., Farid, S., 2023. Comparing asymmetric price efficiency in regional ESG markets before and. Econ. Model. 118, 106095. http://dx.doi.org/10.1016/j.econmod.2022.106095.
Naffa, H., Fain, M., 2021. A factor approach to the performance of ESG leaders and laggards. Financ. Res. Lett. 102073. http://dx.doi.org/10.1016/j.frl.2021.102073.
NSE, 2022. Advances and declines [WWW Document]. URL https://www1.nseindia.com/products/content/equities/equities/historical_advdeclines.htm, (accessed 4.21.22).
OECD, 2020. Ownership structure of listed companies in India.
Paramanik, R.N., Singhal, V., 2020. Analysis of Indian stock market volatility sentiment analysis of Indian stock market volatility. Proc. Comput. Sci. 176, 330–338. http://dx.doi.org/10.1016/j.procs.2020.08.035.
Pesaran, M.H., Shin, Y., Smith, R.J., 2001. Bounds testing approaches to the analysis of level relationships. J. Appl. Econ. 16, 289–326. http://dx.doi.org/10.1002/jae.616.
Piñeiro-chousa, J., López-cabarcos, M.Á., Caby, J., Šević, A., 2021. The influence of investor sentiment on the green bond market. Technol. Forecast. Soc. Change 162, 120351. http://dx.doi.org/10.1016/j.techfore.2020.120351.
Plastun, A., Bouri, E., Gupta, R., Ji, Q., 2022. Price effects after one-day abnormal returns in developed and emerging markets: ESG versus traditional indices. North Am. J. Econ. Financ. 59, 101572. http://dx.doi.org/10.1016/j.najef.2021.101572.
Rakovská, Z., 2021. Composite survey sentiment as a predictor of future market returns: Evidence for german equity indices. Int. Rev. Econ. Financ. 73, 473–495. http://dx.doi.org/10.1016/j.iref.2020.12.022.
Sabbaghi, O., 2022. The impact of news on the volatility of ESG firms. Glob. Financ. J. 51, 100570. http://dx.doi.org/10.1016/j.gfj.2020.100570.
Sachs, J., Kroll, C., Lafortune, G., Fuller, G., Woelm, F., 2021. Sustainable Development Report 2021, http://dx.doi.org/10.1017/9781009106559.
SEBI, 2021. Reports & statistics [WWW Document]. URL https://www.sebi.gov.in/reports-and-statistics.html, (accessed 8.23.21).
Shaikh, I., 2021. On the relationship between policy uncertainty and sustainable investing. J. Model. Manag. http://dx.doi.org/10.1108/JM2-12-2020-0320.
Shin, Y., Yu, B., Greenwood-Nimmo, M., 2014. Modelling asymmetric cointegration and dynamic multipliers in a nonlinear ARDL framework. In: Festschrift in Honor of Peter Schmidt. pp. 281–314.
Shleifer, A., Vishny, R.W., 1997. A survey of corporate governance. J. Finance 52, 737–783. http://dx.doi.org/10.4324/9780203940136.
Tiwari, A.K., Abakah, E.J.A., Bonsu, C.O., Karikari, N.K., Hammoudeh, S., 2022. The effects of public sentiments and feelings on stock market behavior: Evidence from Australia. J. Econ. Behav. Organ. 193, 443–472. http://dx.doi.org/10.1016/j.jebo.2021.11.026.
Umar, Z., Gubareva, M., 2021. The relationship between the Covid-19 media coverage and the environmental, social and governance leaders equity volatility: a time-frequency wavelet analysis. Appl. Econ. 53, 3193–3206. http://dx.doi.org/10.1080/00036846.2021.1877252.
Umar, Z., Gubareva, M., Khoa, D., Teplova, T., 2021. Impact of the Covid-19 induced panic on the environmental, social and governance leaders equity volatility: A time-frequency analysis. Res. Int. Bus. Financ. 58, 101493. http://dx.doi.org/10.1016/j.ribaf.2021.101493.
Vuong, N.B., 2022. Investor sentiment, corporate social responsibility, and financial performance: Evidence from Japanese companies. Borsa Istanbul Rev. 22, 911–924. http://dx.doi.org/10.1016/j.bir.2022.06.010.
Vural-Yavaş, Ç., 2021. Economic policy uncertainty, stakeholder engagement, and environmental, social, and governance practices: The moderating effect of competition. Corp. Soc. Responsib. Environ. Manag. 28, 82–102. http://dx.doi.org/10.1002/csr.2034.
Wang, W., 2018. Investor sentiment and the mean–variance relationship: European evidence. Res. Int. Bus. Financ. 46, 227–239. http://dx.doi.org/10.1016/j.ribaf.2018.02.006.
Wang, G., Yu, G., Shen, X., 2021. The effect of online environmental news on green industry stocks: The mediating role of investor sentiment. Physica A 573, 125979. http://dx.doi.org/10.1016/j.physa.2021.125979.
Woldeamanuel, M., Nguyen, D., 2018. Perceived benefits and concerns of autonomous vehicles: An exploratory study of millennials' sentiments of an emerging market. Res. Transp. Econ. 71, 44–53. http://dx.doi.org/10.1016/j.retrec.2018.06.006.
Xu, Q., Wang, L., Jiang, C., Zhang, X., 2019. A novel UMIDAS-SVQR model with mixed frequency investor sentiment for predicting stock market volatility. Expert Syst. Appl. 132, 12–27. http://dx.doi.org/10.1016/j.eswa.2019.04.066.
Yahya, M., Kanjilal, K., Dutta, A., Salah, G., Ghosh, S., 2021. Can clean energy stock price rule oil price? New evidences from a regime-switching model at first and second moments. Energy Econ. 95, 105116. http://dx.doi.org/10.1016/j.eneco.2021.105116.
Yoo, S., Managi, S., 2021. Disclosure or action: Evaluating ESG behavior towards financial performance. Financ. Res. Lett. 102108. http://dx.doi.org/10.1016/j.frl.2021.102108.