Received 2 September 2022
Revised 4 December 2022
Accepted 20 February 2023

Investor reaction to ESG news sentiment: evidence from South Africa

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Abstract

Purpose – Utilising a database that distinctly classifies firm-level ESG (environmental, social and governance) news sentiment as positive or negative, the authors examine the information flow between the two types of ESG news sentiment and stock returns for 20 companies listed on the Johannesburg Stock Exchange between 2015 and 2021.

Design/methodology/approach – The authors use Shannonian transfer entropy to examine whether information significantly flows from ESG news sentiment to stock returns and a modified event study analysis to establish how stock prices react to changes in the two types of ESG sentiment.

Findings – Using Shannonian transfer entropy, the authors find that for the majority of the companies studied, information flows from the positive ESG news sentiment to stock returns while only a minority of the companies exhibit significant information flow from negative ESG news sentiment to returns. Furthermore, the study's findings show significantly positive (negative) abnormal returns on the event date and beyond for both upgrades and downgrades in positive ESG news sentiment.

Originality/value – This study is among the first in an African context to investigate the impact of ESG news sentiment on stock market returns at high frequencies.

Keywords Green finance, JSE, Transfer entropy, Sustainable investing, Behavioural finance

Paper type Research paper

1. Introduction

Financial markets offer a platform for information competition, and investors are known for collecting, processing and using the information for asset allocations. The advent of electronic trading has increased calls for both quality and timeliness of information for investment decisions. Electronic trading has also increased the importance attached to real-time market data as well as news that feeds into trading decisions. Traders compete for information with several others in financial markets, and the proliferation of textualization techniques has led to more investors resorting to sentiment from business news in their investment decisions (Nyakurukwa & Seetharam, 2023). Different types of sentiment from textual analysis have been used in various studies including social media, traditional news media and message boards. One of the main types of news that investors are increasingly attaching value to in their investing decisions is news on companies' environmental, social and governance (ESG) factors. Though many studies (such as Heston & Sinha, 2017) have explored the effect sentiment from general news has on stock returns, little has been done specifically on how ESG sentiment affects stock returns at high frequencies in an African context.

JEL Classification — C58, G41, M14, Q56

EconomiA
Vol. 24 No. 1, 2023
pp. 68-85
Emerald Publishing Limited
e-ISSN: 2358-2820
p-ISSN: 1517-7580
DOI 10.1108/ECON-09-2022-0126

ESG issues have received increased attention from scholars of late, and regulators are increasingly seeking an understanding of how information flows from ESG news to stock returns and how investors react to this information. Our study is two-pronged: first, we seek to examine the information flow between ESG news sentiment and stock returns and second, we seek to establish how stock prices react to the different types of ESG news sentiment. We use a database that distinctly classifies ESG news sentiment into "positive" and "negative" sentiment. Traditionally, scholars have turned to causality analysis to understand the information transmissions between data series. However, this has been criticised for its lack of robustness in the presence of nonlinearities and structural breaks. We deploy transfer entropy, an econometric model that is increasingly being used in economics and finance to justify the coupling between two time series. The choice of transfer entropy has also been motivated by how it treats information, a treatment that is close to how traders make trading decisions in reality (Liu, Chen, Yang, & Hawkes, 2020).

Our second aim is to investigate how stock prices react to ESG news sentiment. Most of the studies that have been done on the relationship between ESG news and stock market features have been done in the developed world (such as Capelle-Blancard & Petit, 2019; Krüger, 2015), and most of these studies have reported a positive (negative) reaction of stock prices to positive (negative) ESG news with positive ESG news sentiment having a more pronounced effect on returns. We seek to investigate whether the asymmetric effect of ESG news sentiment on stock returns obtains in the emerging market of South Africa, which has distinct characteristics from the developed world. To achieve this, we use Patnaik, Shah and Singh's (2012) modified extreme event method using a database from Bloomberg Inc. In summary, our results show that the majority of the sampled companies exhibited the significant information flow from positive ESG news sentiment compared to negative ESG news sentiment. This signals that positive ESG news sentiment could be important for price formation on the Johannesburg Stock Exchange. Since the results show significant information flow from positive ESG sentiment, further analysis of how stock prices react to positive ESG news sentiment shows that returns react positively (negatively) to positive (negative) changes in positive ESG news sentiment. Since most of the companies that constituted the sample of the study are large companies in the basic materials industry, companies that are investing heavily in ESG factors, we presume that the positive investment in ESG factors serve as a *"goodwill reservoir"* in crisis periods leading to the nonsignificant reaction of stock returns to negative ESG news sentiment.

Our study adds to the growing literature on ESG news sentiment in the stock market in several ways. First, we investigate the information flow between the ESG news sentiment and stock returns using transfer entropy, an econometric model that is model-free and robust in the presence of non-linearities and structural breaks, a significant departure from most empirical studies that use Granger-based causality. Second, we use Patnaik, Shah and Singh's (2012) modified extreme event study analysis which uses the bootstrap approach for hypothesis testing rather than classical statistics. This approach does not assume any distributional properties like normality and is robust in the presence of serial correlation. Unlike prior literature, we show that investors react positively to positive news while the reaction is insignificant for negative news. Moreover, to the best of our knowledge, this is the first study to examine the relationship between ESG sentiment and stock returns in the context of information flows.

The rest of the study proceeds as follows: Section 2 reviews related literature, Section 3 outlines the methodology used in the study, Section 4 presents the results and Section 5 discusses the results while Section 6 concludes.

2. Literature review

Literature shows two theories that demonstrate the effects of media coverage on the behaviour of market participants in capital markets: the *salience view* and the *information view*. The *information view* states that media reduces the cost of acquiring information leading to more quality decisions from investors (Solomon, Soltes, & Sosyura, 2014). This theory is in line with the findings of Bushee, Core, Guay and Hamm (2010) who report that media coverage around earning notices significantly reduces information asymmetry. Blankespoor, Miller and White (2014) also report that companies that distribute information through online platforms contribute to reduced information asymmetry. The *information view* postulates that because news reduces information asymmetry, news sentiment is therefore not likely to lead to a significant reaction from stock prices.

On the other hand, the *salience view* postulates that coverage by media shifts investors' attention to particular stocks (Solomon *et al.*, 2014). Increased coverage of specific stocks in the media leads to increased demand for such stocks. Da, Engelberg and Gao (2011) report that attention-grabbing stocks yield first-day returns after initial public offerings. Solomon *et al.* (2014) examined fund portfolios and reported that those funds holding stocks with high attention draw greater investment than funds with tickers of invisible stocks. The *salience view, therefore,* goes against the efficient market hypothesis as the media can be used by investors to get risk-adjusted returns above the market.

Several studies have been done on the impact of ESG news on firm value often reporting mixed results. Different econometric methodologies have been deployed by scholars to examine whether the stock market reacts to ESG news sentiment. While most of these studies have produced mixed results, the majority of the studies have reported positive (negative) reactions to positive (negative) ESG news (e.g. Wang, Sun, Ma, Xu, & Gu, 2014). However, McWilliams and Siegel (2000) argue that in terms of theory, the marginal costs and marginal benefits of ESG should cancel each other in equilibrium. Thus, with this thinking, the relationship between ESG news and stock market features like stock returns should be insignificant. Capelle-Blancard and Petit (2019) corroborate this line of thinking by asserting that the increased frequency of ESG news does not guarantee a significant impact on the value of the firm.

Studies that have distinctly classified ESG news sentiment have emphasised the asymmetric effects of positive ESG news and negative ESG news. Traditionally, scholarly research in behavioural economics has reported asymmetric responses to positive and negative information (Schepers, 2006). According to Capelle-Blancard and Petit (2019), ESG-positive events are more diverse compared to ESG-negative events which are more persuasive, and as a result, the impact on stock returns is likely to be highly asymmetric. Krüger (2015) investigates the impact of positive ESG news *vis-à-vis* negative ESG news events and reports that negative ESG news events are significantly followed by a stock price decrease while the impact of positive ESG news events is insignificant and depends on how firms relate with their stakeholders. Generating media hype on its own is not sufficient to move the market. Serafeim and Yoon (2021) use a sample of 109 014 firm-day observations of 3109 companies to investigate their reaction to different ESG news. The study reported that firms react to financially material ESG news and that the reaction is more pronounced for positive news. La Torre, Mango, Cafaro and Leo (2020) use 46 publicly listed companies on the Euro STOXX 50 to determine whether their efforts towards ESG management influence stock prices. Their results revealed that the sampled companies' performance did not seem to be affected by ESG commitments.

de Vincentiis (2022) adopt an international dimension to establish whether the effect of ESG-related news on stock returns is location-specific. Using the classic event study methodology, the study reports that ESG news is interpreted differently in different geographic locations. de Vincentiis (2022) found that in Europe, bad news is more influential than good news, resulting in a negative price impact. The opposite was reported for the USA, where it was reported that good news has a more pronounced effect negative effect on stock returns. In the Asia Pacific region, ESG news sentiment was reported to be insignificantly related to stock returns. Sabbaghi (2022) employs an EGARCH (exponential generalised autoregressive conditional heteroskedastic) framework to determine the effect of good news and bad news on stock volatility. Their analysis provides empirical evidence in support of the hypothesis that the impact of news on the volatility of ESG firms is larger for bad news, compared to good news. The findings also provide evidence of a slow response by small-size firms to news in an ESG context. Khan (2019) utilises previous literature on ESG materiality to develop a new ESG metric. The new metric predicted stock returns in a global investable universe over the tested period, suggesting potential investment value in ESG signals.

Another strand of literature has explored the role of reputation in the relationship between ESG news and stock returns. Werther and Chandler (2005) postulate that in bad times, good ESG serves as a *"reservoir of goodwill"*. Thus, it is expected that firms with a good reputation will experience a lower or insignificant decrease in their market values upon the release of negative ESG news. Conversely, Baron (2008) asserts that companies that are highly visible in the ESG space with high ESG scores are likely to receive more public scrutiny and may experience significantly negative returns in times of crisis.

3. Methodology

3.1 Data

The study utilises firm-level data for all Johannesburg stock exchange (JSE) All Share Index (JALSH) constituent firms for the period 1 January 2015 to 30 August 2021. Firm-level daily data on positive ESG news sentiment, negative ESG news sentiment and closing prices of stocks are extracted from the Bloomberg terminal. Returns are adjusted for corporate actions and/or dividends where applicable. Only the current JALSH constituent companies are included in the study as they are the only companies for which ESG news sentiment data are available on the Bloomberg terminal. This means companies that were part of the JALSH during the sample period but exited the index before 30 August 2021 are excluded from the analysis. The initial database containing the firm-level data for ESG news sentiment, closing stock prices and closing JALSH prices consisted of 140 companies. The second stage involved removing companies that did not have any ESG news sentiment data from the database. The majority of the companies did not have any ESG news data for the duration of the sample period. This led to the removal of 120 companies, leading to a final database that contained 20 companies with non-missing daily ESG news sentiment data. A list of the companies that formed the final sample used in this study is shown in Table 1:

Table 1 shows the full list of the companies that formed the sample for this study. It can be seen that the majority of the companies are in the basic materials industry and are particularly mining companies.

3.2 Variables

3.2.1 ESG sentiment. Bloomberg computes two types of ESG news sentiment, namely positive ESG news sentiment as well as negative ESG news sentiment. Bloomberg skims through more than 80,000 news stories covering ESG issues. This includes the search for exclusive content from Bloomberg Media Group as well as content from press releases and reports from governments, industries, stock markets and other groups. Positive ESG news sentiment is defined as a *z-score* representing a change in positive ESG behaviour relative to the past 30 days. Negative ESG sentiment is defined as the *z-score* representing a change in negative ESG behaviour relative to the past 30 days. The sentiment values are produced by a

Table 1.
List of sample companies

	Ticker symbol	Official company name	Industry
1	AGL	Anglo American plc	Basic materials
2	AMS	Anglo American Platinum Ltd	Basic materials
3	ANG	AngloGold Ashanti Ltd	Basic materials
4	EXX	Exxaro Resources Ltd	Basic materials
5	GFI	Gold Fields Ltd	Basic materials
6	GLN	Glencore plc	Basic materials
7	HAR	Harmony Gold Mining Company Ltd	Basic material
8	IMP	Impala Platinum Holdings Ltd	Basic materials
9	JSE	JSE Ltd	Financials
10	MUR	Murray & Roberts Holdings Ltd	Industrials
11	NED	Nedbank Group Ltd	Financials
12	NHM	Northam Platinum Limited	Basic materials
13	RBP	Royal Bafokeng Platinum Ltd	Basic materials
14	REM	Remgrow Ltd	Financials
15	SAP	Sappi Ltd	Basic materials
16	SBK	Standard Bank Group Ltd	Financials
17	SHP	Shoprite Holdings Ltd	Consumer services
18	SSW	Sibanye Stillwater Ltd	Basic materials
19	TBS	Tiger Brands Ltd	Consumer goods
20	WBO	Wilson Bayly Holmes - Ovcon Ltd	Industrials

Source(s): Authors' compilations from https://www.jse.co.za/

machine learning model trained by Bloomberg analysts to describe firm behaviour as positive, negative or neutral from an investor's perspective. Positive sentiment values and news story counts show that firms are participating in positive ESG actions and events while negative sentiment values and story counts show that companies are participating in negative actions and events. Examples of the news generating positive ESG news sentiment and negative ESG news sentiment as explained on the Bloomberg website include the following respectively:

> Decreasing energy consumption, introducing products that address environmental and social issues, winning favourable legal rulings or improving diversity and inclusion

> Violating environmental and labour laws, harming the natural environment, losing lawsuits or failing to acknowledge or manage risks

The *z-score* that shows the change in positive and negative ESG sentiment is computed as follows:

$$z - score = \frac{Positive\ (Negative)\ count - 30\ day\ mean\ positive\ (Negative)\ count}{Standard\ deviation\ for\ 30\ day\ positive\ (Negative)\ day\ count}$$

where positive (negative) count is the number of ESG news stories projected to have a positive (negative) sentiment on a specific day.

3.2.2 Stock and market returns. Stock returns ($R_{i,t}$) for stock i at time t are calculated as follows:

$$R_{i,t} = ln\left(\frac{P_t}{P_{t-1}}\right) \quad (1)$$

where P_t stands for the closing price at time t and P_{t-1} stands for the closing price at time $t - 1$.

3.3 Econometric models

3.3.1 Transfer entropy. Entropy-based methodologies have become popular in economics and finance since they were first used by Schreiber (2000). Transfer entropy was used as the basis for this study because of its robustness compared to traditional Granger causality tests, especially at the tails of return distributions (Wang & Wang, 2021). Transfer entropy is a model-free measure that can evaluate the flow of information between random variables in a time-directed manner. Thus, it provides an asymmetrical approach to measuring information transfer (Yao, 2020). The specific details of the computation and measurement of the statistics used in the two types of transfer entropy used in this study are outlined in the following subsections [1].

3.3.1.1 Shannonian transfer entropy. Assuming that *log* denotes the logarithm of a number to base 2, Shannon entropy (Shannon, 1948) postulates that for a discrete random variable J with probability distribution $p(j)$ where j stands for the various outcomes J can take, the average number of bits required to encode the independent draws from the distribution of J optimally can be calculated as follows:

$$H_J = -\sum p(j)\,.log\,\left(p\left(j\right)\right) \tag{2}$$

Effectively, the formula in Equation (2) quantifies the uncertainty which increases with the number of bits needed to optimally encode a sequence of realisations of J. Measurement of the flow of information between two time series is achieved by combining the concept of Shannon entropy with the concept of Kullback–Liebler distance (Kullback & Leibler, 1951) coupled with an assumption that the underlying process evolves through a Markov process (Schreiber, 2000). Allowing I *and* J to denote two discrete random variables with marginal probability distributions $p(i)$ and $p(j)$, respectively, as well a joint distribution $p(i,j)$ whose dynamical structures correspond to stationary Markov processes of order k *and* j, the Markov property implies that the probability to observe I at time $t+1$ in state i conditional on the k previous observations is as follows:

$$p(i_{t+1}|i_t,\ldots,i_{t-k+1}) = p(i_{t+1}|i_t,\ldots,i_{t-k}) \tag{3}$$

The average number of bits needed to encode the observation in $t+1$ if the previous k values are known is given by

$$h_1(k) = -\sum p\left(i_{t+1}, i_t^{(k)}\right)\,.log\,\left(p\left(i_{t+1}\middle|i_t^{(k)}\right)\right) \tag{4}$$

where $i_t^{(k)} = (i_t,\ldots,i_{t-k+1})$. $h_j(l)$ can be derived analogously for process J. In a bivariate specification, the flow of information from one process (J) to another process (I) is calculated by finding the departure from the generalised Markov property $p(i_{t+1}\left|i_t^{(k)}\right.) = p(i_{t+1}\left|i_t^{(k)}, j_t^{(l)}\right.)$ using the Kullback–Leibler distance (Schreilber, 2000). The Shannon transfer entropy is quantified using the following formula:

$$T_{J\to I}(k,l) = \sum_{i,j} p\left(i_{t+1}, i_t^{(k)}, j_t^{(l)}\right)\,.\,log\left(\frac{p\left(i_{t+1}\middle|i_t^{(k)}, j_t^{(l)}\right)}{p\left(i_{t+1}\middle|i_t^{(k)}\right)}\right) \tag{5}$$

where $T_{J\to I}$ measures the flow of information from one process J to another process I. ($T_{I\to J}$ measures the flow of information from I to J and can be derived analogously).

3.3.1.2 Effective transfer entropy. The transfer entropy represented by Equation (5) can produce biased estimates as a result of small sample effects. This is ameliorated by the use of the effective transfer entropy proposed by Marschinski & Kantz (2002) and is computed as follows:

$$ET_{J \to I}(k,l) = T_{J \to I} - T_{Jshuffled \to I}(k,l) \tag{6}$$

where $T_{Jshuffled \to I}(k,l)$ indicates the transfer entropy using a shuffled version of the time series of J. Shuffling in this case involves drawing values from the time series of J at random and realigning them to generate a new series. The process of shuffling extinguishes the time series dependencies of J and the statistical dependencies between I *and* J. Consequently, $T_{Jshuffled \to I}(k,l)$ converges to zero with increasing sample size, and any non-zero value of $T_{Jshuffled \to I}(k,l)$ is due to the small sample size. A consistent estimator is therefore achieved by shuffling multiple times and subsequently averaging the transfer entropy estimates across all replications. This average is then subtracted from the Shannon transfer entropy estimates to get the effective transfer entropy estimates which are bias-corrected. The statistical significance of the transfer entropy estimates is derived using a Markov block bootstrap proposed by Dimpfl and Peter (2013), which maintains the dependencies within the time series, contrary to the shuffling process outlined above. The Markov block bootstrap generates the distribution of transfer entropy estimates under the null hypothesis of no information. Shannonian transfer is then estimated using the simulated time series. This process is repeated, thereby yielding a distribution of the entropy transfer estimate under the null hypothesis of no information flow. The *p-value* associated with the null hypothesis of no information transfer is given by $1 - \hat{q}_{TE}$, where $\hat{q}_{TE}$ denotes the quantile of the simulated distribution that corresponds to the original transfer entropy estimate.

It can be noted that the calculation of Shanonian entropy is based on discrete data. Because this study uses continuous stock returns, these data are discretised using symbolic coding. This is achieved by partitioning the data into a finite number of bins based on the quantiles of the empirical distribution of the data. Assuming the bounds specified for the n bins are represented by $q_{1,}q_2, \ldots, q_n$ where $q_1 < q_2 \ldots < q_n$ and assuming that a time series is denoted by y_t, the data are recoded by

$$\begin{cases} 1 & for\, y_t \leq q_1 \\ 2 & for\, q_1 < y_t \leq q_2 \\ \vdots & \vdots \\ n-1 & for\, q_{n-1} < y_t \leq q_2 \\ n & for\, y_t \geq q_n \end{cases}$$

Each value in the time series y_t is replaced by an integer $(1, 2, \ldots, n)$ according to how S_t relates to the interval specified by the lower and upper bounds q_1 *to* q_n. The choice of bins is justified by the empirical distribution of the data.

3.3.2 Event study methodology. In classical event study papers within economics and finance, an event is identifiable and can be traced to a specific point in time. Examples of these identifiable events include the announcement of a merger or a dividend. More recently, instead of events being specifically identifiable, they can also be spread out such as the introduction of a specific policy, for example, trade liberalisation, or they can be defined by spike values of a particular variable (Ranco, Aleksovski, Caldarelli, Grčar, & Mozetič, 2015). In this study, we define events in line with Patnaik, Shah and Singh (2012) where event dates are defined as those on which extreme values of ESG news sentiment are observed. This involves scanning the positive (negative) ESG news sentiment values and identifying the dates on which the one-day values were in the tails. The important question that should be answered in adopting the above-mentioned definition of event dates is how extreme our extreme cases should be defined.

Following the statistical tradition of using 5% as the standard level of significance in hypothesis testing, we define extreme events to be those in the upper and lower 2.5% tails of the distribution. From the literature reviewed on the application of event study methodologies to studies using daily investor sentiment proxies, there seems to be some level of arbitrariness in the choice of pre-event and post-event periods. We settle for pre-event and post-event windows of 10 days. We believe 10 days is sufficiently long to identify either pre-emptive or reactive movements for extreme changes in ESG news sentiment.

We calculate returns as the log difference of the closing prices of each ticker. The stock returns are estimated using Equation (1). Since in the event study we are not interested in normal returns, but abnormal returns, we compute abnormal returns using the market model as follows:

$$AR_{it} = R_{it} - E(R_{it}) \tag{7}$$

where R_{it} is the realised return for stock i on day t, and $E(R_{it})$ is the expected return of the stock. We estimate the expected return based on an OLS-regressed market model ($AR^{market\ model}$) as follows:

$$E(R_{it}) = \alpha + \beta_i(R_{mt}) + \mu_{it}\, for\ t = 1, 2, 3, \ldots, T \tag{8}$$

where α is the intercept term, βi is the slope of the coefficient, μit is the standard error term and T is the number of periods in the estimation period. Following common practice (e.g. Sprenger, Sandner, Tumasjan, & Welpe, 2014), we use a 120-day estimation period starting 130 days before the relevant date to not overlap with the event window of our event study. We calculate cumulative abnormal returns (CAR) from τ_1 to τ_2 as follows:

$$CAR_i(\tau_1, \tau_2) = \sum_{t=\tau_1}^{t=\tau_2} AR_{it} \tag{9}$$

While the cumulative abnormal average returns (CAAR) across the N firms are computed as follows:

$$CAAR(\tau_{1,}\tau_2) = \frac{1}{N}\sum_{i=1}^{N} CAR_i(\tau_{1,}\tau_2) \tag{10}$$

When it comes to statistical inference, one of the weaknesses of using classical statistics often used in traditional event studies are the distribution assumptions like normality and lack of serial correlation. We alleviate this weakness of using classical statistics in event studies by using the bootstrap method. This approach does not require any distributional assumptions like normality and is robust against serial correlation. We follow Patnaik *et al.* (2012) by using the bootstrap approach as follows:

(1) Suppose there are N events. Each event is expressed as a time series of cumulative returns (CR) within the event window. The overall summary statistic of interest is the average of all the CR time series;

(2) We create bootstrap samples using sampling with replacement, N times within a dataset of N events. For each event, its corresponding CR time series is taken. This yields a time-series CR, which is one draw from the distribution of the statistic and

(3) This procedure is repeated 1,000 times to obtain the full distribution of CR. Percentiles of the distribution are created, giving bootstrap confidence intervals for our estimates.

4. Results and discussion

4.1 Descriptive statistics

Before presenting results from the econometric models, we first present the descriptive statistics to show the distributional characteristics of the study variables. We first show the Pearson correlation matrix in Table 2 to show the bivariate relationships among the variables.

The correlation matrix shown in Table 2 shows that the pairwise correlations between the variables are all very low. The correlation between positive ESG news sentiment and stock returns is positive and statistically significant at the 5% level showing a direct association between positive ESG news sentiment and stock returns. As expected, the correlation between negative ESG news sentiment and stock returns is negative but only marginally significant *($p < 0.1$)*. The significant correlations between ESG news sentiment and stock returns in Table 2 show that there could be important relationships among the variables that need to be further explored using formal econometric models. Table 3 shows the summary statistics of the variables used in the study.

The summary statistics are presented in two phases: first for the entire database that includes all the observations and second, a database that excludes observations where there is a change in the ESG news sentiment of 0 (representing neutral ESG news sentiment). This is done because the whole database shows considerable observations with neutral sentiment, and only looking at the whole database might hide some important trends in the data. Table 3 shows that the mean for positive ESG news sentiment is considerably higher than the mean for negative ESG news sentiment using both samples. The next section presents and

	Pos ESG	Neg ESG	Return	JALSH ret
Pos ESG	1.0000	0.0905***	0.0129**	0.0060
Neg ESG	0.0905***	1.0000	−0.0087*	0.0027
Firm return	0.0129**	−0.0087*	1.0000	0.0343***
JALSH ret	0.0060	0.0027	0.0343***	1.0000

Note(s): The table shows the pairwise Pearson correlation coefficients of the variables, *, ** and *** show statistical significance at the 10, 5 and 1% level, respectively
Source(s): Authors' estimations

Table 2. Pearson correlation matrix

	Mean	SD	Min	Max
Whole database				
Pos ESG	0.0048	0.3877	−0.6707	0.4684
Neg ESG	0.0025	0.4688	−0.2666	−0.0109
Firm return	0.0003	0.0293	−0.3071	0.4684
JALSH ret	0.0002	0.0115	−0.1022	0.0726
Excluding neutral sentiment				
Pos ESG	0.0373	1.0772	−0.6707	0.4684
Neg ESG	0.0117	1.0157	−0.2666	−0.0109

Note(s): Table 3 shows the summary statistics of the variables used in the study. SD shows the standard deviation, Min shows the minimum value and Max shows the maximum value. The first panel gives the summary statistics for the entire database while the second panel presents the summary statistics of a database that excludes observations with a neutral sentiment (a change of 0 in ESG news sentiment)
Source(s): Authors' estimations

Table 3. Summary statistics

discusses the results from the econometric models used to determine the information flow between ESG news sentiment and stock returns.

4.2 Transfer entropy

The strength of using transfer entropy in time series analysis is that the method is model-free and robust to nonlinearities and structural breaks in the data. First, to establish whether the time series are nonlinear, the Brock, Brock, Hsieh, LeBaron and Brock (1991) (BDS) test is applied on the residuals from the stock return equation involving one lag each of positive ESG news sentiment and negative ESG news sentiment, respectively, for each of the 20 companies that formed part of the sample used in this study. The results of the BDS test are presented in Table A1 in Appendix A. As shown in Table A1, there is ample evidence of the existence of nonlinearities in the residuals of the stock return equations of the 20 companies. Thus, the use of transfer entropy is expected to produce reliable results even in the presence of tail dependencies. Table 4 shows the findings on the information flow between ESG news sentiment and stock returns for all the 20 companies.

Several issues can be observed from the findings on the possible information flow from positive (negative) ESG news sentiment to stock returns. Starting with positive ESG news sentiment, there is statistically significant information flow from positive ESG news sentiment to stock returns for 12 out of the 20 companies in the sample, constituting 60% of the total sample used in the study. However, the effective transfer entropy values are all very low (less than 0.009) on a scale of 0 to 1 showing that though there is significant information

		Positive ESG news sentiment			Negative ESG news sentiment		
	TICKER	TE	Std.err	Eff.TE	TE	Std.err	Eff.TE
1	AGL	0.0128***	0.0019	0.0075	0.0075**	0.0017	0.0027
2	AMS	0.0055	0.0016	0.0020	0.0030	0.0016	0.0000
3	ANG	0.0078**	0.0018	0.0034	0.0075**	0.0016	0.0025
4	EXX	0.0022**	0.0018	0.0000	0.0043*	0.0014	0.0008
5	GFI	0.0131***	0.0016	0.0090	0.0067	0.0017	0.0020
6	GLN	0.0131***	0.0016	0.0090	0.0039	0.0019	0.0000
7	HAR	0.0113***	0.0018	0.0065	0.0034	0.0017	0.0000
8	IMP	0.0030	0.0015	0.0000	0.0024	0.0015	0.0000
9	JSE	0.0065**	0.0015	0.0029	0.0001	0.0006	0.0000
10	MUR	0.0002	0.0009	0.0000	0.0002	0.0006	0.0000
11	NED	0.0046	0.0017	0.0007	0.0003	0.0008	0.0000
12	NHM	0.0092***	0.0017	0.0056	0.0005	0.0010	0.0000
13	RBP	0.0016	0.0008	0.0011	0.0002	0.0007	0.0000
14	REM	0.0000***	0.0000	0.0000	0.0000***	0.0000	0.0000
15	SAP	0.0036	0.0017	0.0000	0.0000***	0.0000	0.0000
16	SBK	0.0057	0.0019	0.0007	0.0037	0.0017	0.0000
17	SHP	0.0000***	0.0000	0.0000	0.0068	0.0016	0.0027
18	SSW	0.0030	0.0004	0.0000	0.0058	0.0019	0.0005
19	TBS	0.0002**	0.0007	0.0000	0.0041	0.0015	0.0000
20	WBO	0.0000***	0.0000	0.0000	0.0000***	0.0000	0.0000

Note(s): The table shows the transfer entropy from positive (negative) ESG news sentiment to stock returns. The direction of possible information flow is from ESG news sentiment to stock returns. Shannon transfer entropy is given in the TE column. Effective transfer entropy estimates can be found in the Eff.TE column. Standard errors and statistical significance are based on the bootstrap samples. The TE estimates are compared to the quantiles of the bootstrap samples to calculate p-values. *, ** and *** represent statistical significance at the 10, 5 and 1%, respectively
Source(s): Authors' estimations

Table 4. Results from Shannonian entropy

flow from positive ESG news sentiment to stock returns, the magnitude of the information flow is minimal. When it comes to negative ESG news sentiment, significant information flow from negative ESG news sentiment and stock returns only exist for 6 out of the 20 companies analysed. This is only 30% of the companies analysed and shows that for the majority of the companies, the information flow from the negative ESG news sentiment to stock returns is insignificant. It can also be noted that for those few companies that have significant information flow from negative ESG news sentiment to stock returns, the effective transfer entropy values are lower in absolute terms compared to the values for positive ESG sentiment. This shows that besides there being more companies having significant information flow from positive ESG sentiment to stock returns than negative ESG news sentiment, the ETE values are also comparatively lower. It is also interesting to note that as expected, for all the 20 companies analysed, there is no significant information flow from stock returns to both positive and negative ESG news sentiment. The results are not displayed for brevity but are available upon request.

4.3 Event study

Before we present the results on the market reaction to ESG news events, we show the distribution of the extreme ESG news events in Table 5. As explained earlier in the methodology section, extreme events were defined as those in the upper and lower 2.5% tails of the distribution. In Table 5, positive ESG sentiment events include all the extreme events which either led to a positive or negative change in positive ESG news sentiment from the previous 30-day average. Negative ESG events are all the events in the tail of the distribution that either led to positive or negative changes in negative ESG news sentiment from the previous 30-day average. Because the results from the Shannonian transfer entropy have mainly shown that it is positive ESG news sentiment that significantly flows to stock returns, concentrate on positive ESG news only. We further split the positive ESG news sentiment into “Upgrades” and “Downgrades” in positive ESG news sentiment. “Upgrades” in positive ESG sentiment are defined as positive changes in positive ESG news sentiment while “Downgrades” in positive ESG news sentiment are defined as negative changes in positive ESG news sentiment from the 30-day average.

According to Sprenger *et al.* (2014), most event studies, even those that distinguish sentiment, report price reactions on the arrival of new information. In this study, we are mostly interested in showing the clearest signal of the market reaction on the day of the event itself. We however include the effect before and after the event to determine leakage and drift. The results of the market reaction from positive and negative ESG news sentiment are shown in Figure 1.

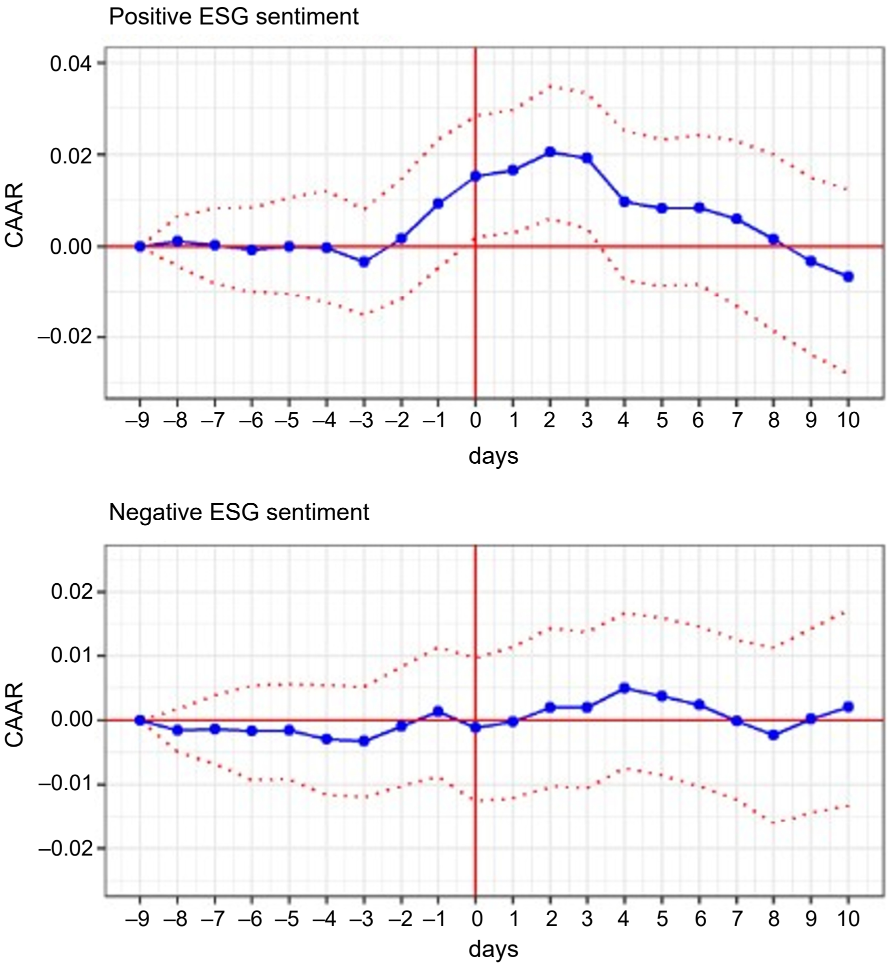
As shown in Figure 1, for positive ESG news sentiment, the 95% confidence bands include 0 for all the nine days before the event date as well as from four days after the event onwards.

Description	*n*
Positive ESG sentiment	229
Negative ESG sentiment	300
Upgrades in Positive ESG sentiment	54
Downgrades in Positive ESG sentiment	83

Note(s): The differences in the positive ESG upgrades (downgrades) events and positive ESG sentiment events are explained by events which do not change (are the same as the previous event) from the previous 30-day average

Source(s): Authors’ compilations from Bloomberg data

Table 5.
Distribution of extreme ESG sentiment events



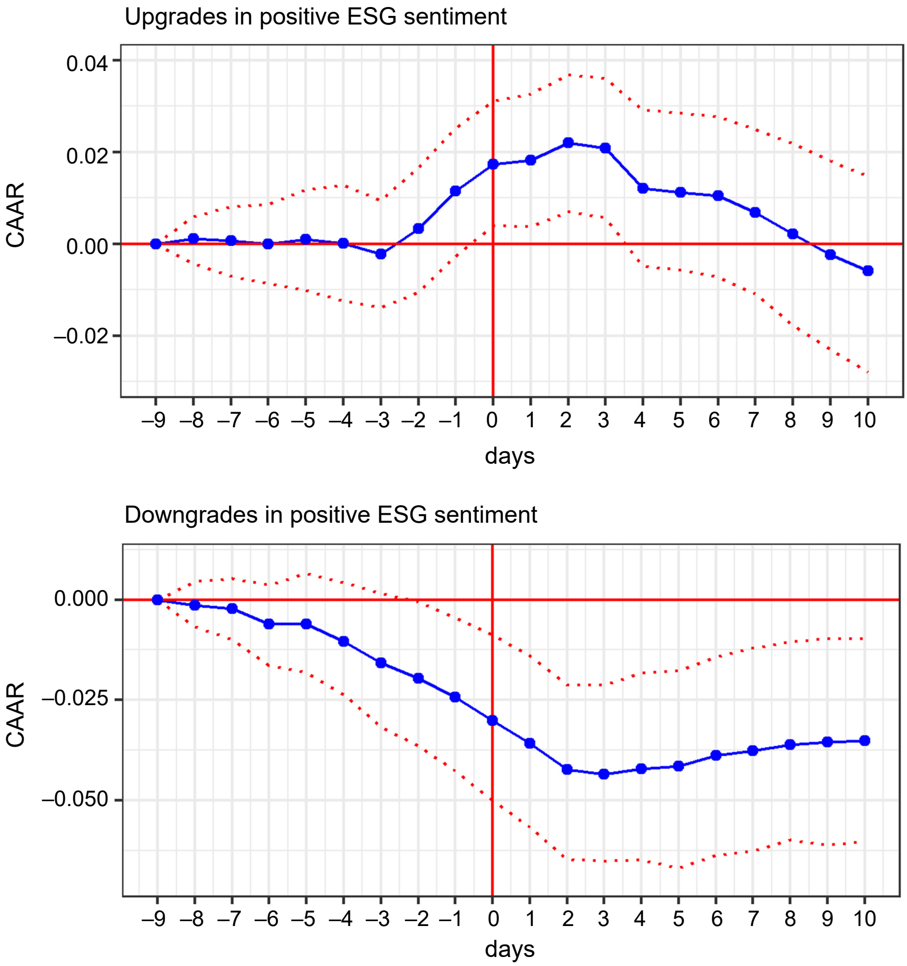
Note(s): The blue line shows the CAARs of identified events while the red dotted lines show the 95% confidence bands

Source(s): Authors' estimations

Figure 1. Market reaction from positive and negative ESG news sentiment

Thus, there is a significant positive reaction to positive ESG news sentiment on the event date up to three days after the event date. When it comes to negative ESG news sentiment, no clear pattern of the CAARs can be seen within the event window. Moreover, the CAARs are not significant at the 5% significance level across the event window. It can therefore be concluded that the market significantly overreacts to positive ESG news sentiment while the negative ESG news sentiment is immediately captured in the stock prices. Splitting the positive ESG news sentiment into "Upgrades" and "Downgrades" as previously defined leads to the market reaction as shown in Figure 2:

Figure 2 shows that upgrades in positive ESG news sentiment produce a market reaction similar to the positive ESG news sentiment shown in Figure 2 Panel A. There is a significant positive reaction to upgrades in positive ESG sentiment on the event day up to three days



Note(s): The blue line shows the CAARs of identified events while the red dotted lines show the 95% confidence bands

Source(s): Authors' estimations

Figure 2. Market reactions to upgrades (downgrades) in positive ESG news sentiment

after the event date. For downgrades in positive ESG news sentiment, Figure 2 shows a significant negative reaction starting from three days before the event up to the end of the event window. From the results presented in Figure 2, it is clear that the market significantly overreacts to positive ESG news sentiment while there is no significant reaction to negative ESG news sentiment as shown by the CAARs, which are not significantly different from zero across the event window.

4.4 Robustness checks

We institute a raft of robustness checks to ensure that our results are not driven by particular specifications. Sprenger *et al.* (2014) argue that the use of different event window periods may generate different results. We test if our results are sensitive to the event window period used by using a five-day and three-day window period. Our results remain qualitatively similar. Stock returns react significantly positively to positive ESG news sentiment and insignificantly to negative ESG news sentiment on the event date.

Secondly, instead of using raw returns, Schmidt (2019) follows Stapleton and Subrahmanyam (1983) by estimating the idiosyncratic component of each individual stock where the log returns of each stock are regressed on the log returns of the market index of each respective day using ordinary least squares. The residual series, representing the log returns of each stock that cannot be explained by the market becomes the idiosyncratic return. First, using transfer entropy, we find significant information flow from positive ESG news sentiment in 11 out of the 20 sampled companies, though the transfer entropy values are also low. When it comes to negative ESG sentiment, a significant flow of information is only reported for 5 out of the 20 companies. These results confirm earlier results showing a more significant flow of information from positive ESG sentiment to stock returns compared to negative ESG sentiment. In the event study model, we also report that investors react more to positive ESG news sentiment compared to negative ESG sentiment.

In our final robustness check, we divide our sample into two subsamples to establish whether COVID-19 has a significant effect on our results. COVID-19 came as a black-swan event that had repercussions on the wider economy and the financial markets in particular because of the uncertainty about how the pandemic would evolve. We follow Nyakurukwa and Seetharam (2023) by using 4 March 2020 as the break date to partition the sample into the pre-COVID-19 and COVID-19 subsamples. The results from transfer entropy for all the subsamples show positive ESG sentiment as more influential in affecting stock returns than negative ESG sentiment. However, in the COVID-19 subsample, we witness slightly more stocks (14) exhibiting a significant flow of information from positive ESG sentiment compared to the pre-COVID-19 subsample (11).

5. Discussion

Our results in the previous section show a significant flow of information from positive ESG news sentiment to stock returns for the majority of the stock tickers with only a few companies showing significant information flow from negative ESG news sentiment to stock returns. This confirms the preliminary results from the Pearson correlation matrix which showed a significant positive correlation between positive ESG news sentiment and stock returns while the relationship between negative ESG news sentiment and stock returns, though negative, was only marginally significant. Our second aim was to examine stock price reactions to the positive (negative) ESG news sentiment. We find significant positive CAR on the event date and three days after the event date for positive ESG news sentiment. Negative ESG news sentiment events do not generate significant CAR across the event window. The results from the analysis depart from previous empirical studies in several ways. First, most studies (e.g Serafeim & Yoon, 2021) have shown that stock prices respond more to negative ESG news sentiment than positive ESG news sentiment. We however report no significant response for negative ESG news sentiment and a significantly positive response for positive ESG sentiment. Our results can be possibly explained by various factors which could offer avenues for future research. The companies that formed part of the sample of this study are predominantly basic materials industry companies, most of which constitute the biggest companies on the JSE by market capitalisation. These companies have invested heavily in ESG-related matters such that even when they report negative ESG sentiment, the investment in ESG made serves as *"goodwill in times of crisis"*. Second, the distribution of the ESG news sentiment shows that negative ESG news sentiment had more non-neutral events as a percentage of the total events compared to positive ESG news sentiment events. This could give a signal that the negative ESG news sentiment events were less compelling than the positive ESG news sentiment events thereby leading to the latter significantly affecting returns (Capelle-Blancard & Petit, 2019). Future studies could examine the sources of the news to untangle the effect of the ESG sentiment from different sources. Capelle-Blancard and Petit (2019) have shown that the news from companies' press releases and some civil society organisations may tone down negative ESG news while accentuating positive ESG news. Finally, the study sample consists mostly of mining companies, which have a concentration of ESG factors related to the environment due to air and water pollution resulting from legacy issues like acid mine drainage and abandoned mines and rectification of the legacy issues might take longer than anticipated. This might explain the insignificant reaction to negative ESG news sentiment especially if investors know that the companies are working towards rectifying the problem in the long run. This is supported by the positive reaction to positive ESG news sentiment showing that though investors do not penalise negative ESG factors, they reward companies that are consciously working towards improving their ESG scores. Our findings, therefore, show that the mixed results from the empirical literature on the effect of ESG sentiment on stock returns could be a result of the different contexts of the studies, for example, the sectors of the companies sampled. Our results also corroborate the findings of de Vincentiis (2022) who suggests that ESG news is interpreted differently in different geographical locations depending on cultural and other context-specific factors. The influential role of positive ESG news sentiment over negative ESG news in price formation in South Africa was also reported in the USA (de Vincentiis, 2022).

6. Conclusion

The study sought to examine whether there is a significant information flow between ESG news sentiment and stock returns and how stock prices react to extreme ESG news sentiment events. Using Shannonian transfer entropy which is robust in the presence of nonlinearities, the findings show that there is significant information flow from positive ESG news sentiment for the majority of the companies while information flow from negative ESG news sentiment is largely insignificant. Using event study analysis, we show that investors react strongly to positive ESG news sentiment while there is no statistically significant reaction to negative ESG news sentiment. Our findings show that shareholders seem to reward positive ESG behaviours but do not penalise bad ESG behaviours. Our sample was mainly dominated by companies in the basic materials industry because of the availability of data. Future studies could investigate the information flow and market reaction to ESG news using an inclusive sample of companies. Since some stocks react more to positive ESG sentiment while others react to negative ESG news sentiment, further studies could also examine whether the differences in these results can be explained by size, liquidity or public exposure.

In terms of policy implication, for asset allocation purposes, it is possible to realise abnormal returns by buying stocks and selling them as soon as they publish extremely positive ESG news. Since investors do not punish negative ESG news events, regulatory authorities could step up and fill this gap by punishing negative ESG events. However, expecting public authorities to act to balance the market is a very debatable topic and from an economic point of view, it is usually inefficient in the long term. The ESG data from Bloomberg employed in the study is not freely available, and the high prices might create a barrier for most investors. To this end, sustainability data could be categorised as a "digital global commons," which would imply that because it is crucial to achieving global sustainable development agenda, it should be made available and freely useable by the general public and the contributing community, much like how everyone can access and use cyberspace. For ESG data, this may follow the Wikipedia format. Global institutions like the United Nations could be instrumental in efforts to realise this. Capelle-Blancard and Petit (2019) have shown that the news from companies' press releases and some civil society organisations may tone down negative ESG news while accentuating positive ESG news. While there are regulatory authorities, like the Press Council, that ensure transparency and adherence to journalistic standards, an ESG-specific regulatory body could be established to oversee ESG-related news to ensure transparency and complete information is disseminated. This would require experts in ESG-related matters to sit on the adjudication panel of such a regulatory body. This will ultimately lead to minimal manipulation of ESG news to achieve specific desired ends.

Note

1. Some information in this section was adapted from Nyakurukwa (2021).

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Appendix

Table A1.
BDS test results

Dimension	Positive ESG news sentiment 2				Positive ESG news sentiment 6				Negative ESG news sentiment 2				Negative ESG news sentiment 6			
Embedding dimension	0.5σ	1σ	1.5σ	2σ	0.5σ	1σ	1.5σ	2σ	0.5σ	1σ	1.5σ	2σ	0.5σ	1σ	1.5σ	2σ
AGL	8.228*	9.347*	10.302*	10.560*	15.872*	16.255*	17.209*	17.321*	2.393*	3.819*	5.659*	7.068*	2.661*	5.000*	6.775*	8.899*
AMS	4.722*	5.507*	6.153*	6.116*	11.312*	10.076*	10.226*	10.936*	4.328*	5.327*	6.241*	6.052*	3.466*	5.946*	7.947*	9.544*
ANG	3.715*	4.729*	5.763*	6.2871*	4.857*	6.7072*	8.523*	9.641*	4.821*	5.058*	5.019*	4.619*	2.448*	6.565*	7.087*	7.159*
EXX	4.634*	4.770*	4.987*	4.945*	5.216*	6.463*	7.271*	7.471*	2.295*	2.004*	2.311*	3.097*	2.329*	3.407*	3.887*	4.617*
GFI	5.402*	6.353*	7.553*	8.168*	7.330*	9.114*	10.781*	11.798*	2.642*	3.691*	4.537*	4.906*	4.399*	6.256*	7.253*	7.923*
GLN	7.794*	9.206*	9.590*	8.378	13.148*	15.746*	17.388*	16.720*	3.239*	3.552*	2.959*	2.087*	4.553*	5.456*	6.441*	6.859*
HAR	4.662*	5.630*	6.823	7.906*	6.617*	7.842*	9.215*	10.562*	3.652*	4.188*	4.689*	4.169*	4.566*	5.531*	6.237*	6.320*
IMP	4.430*	5.386*	6.433*	7.155*	7.430*	8.320*	9.608*	10.964*	3.816*	3.941*	5.304*	5.460*	5.495*	5.909*	8.075*	9.032*
JSE	3.091*	3.873*	4.163*	3.912*	4.227*	6.030*	6.748*	7.154*	4.251*	4.209*	3.452*	1.201*	6.445*	7.213*	6.145*	4.162*
MUR	10.174*	10.247*	10.562*	10.757*	21.016*	14.85*	12.199*	11.271*	6.499*	7.190*	7.179*	6.824*	13.820*	11.178*	9.243*	7.988*
NED	6.486*	8.381*	11.036*	12.937*	12.007*	13.245*	15.080*	16.817*	4.442*	4.994*	5.537*	5.767*	9.7044*	9.509*	9.272*	9.051*
NHM	4.475*	5.562*	6.981*	8.168*	8.185*	7.922*	8.996*	10.608*	4.665*	4.968*	5.433*	5.360*	6.885*	6.286*	7.665*	8.052*
RBP	6.933*	7.494*	8.608*	9.230*	12.253*	11.509*	11.759*	11.949*	5.805*	6.913*	7.769*	7.565*	8.262*	8.992*	10.098*	11.368*
REM	7.438*	8.759*	9.658*	10.631*	12.807*	7.438*	8.759*	9.658*	3.547*	3.991*	4.780*	4.614*	5.648*	6.487*	8.497*	9.362*
SAP	8.492*	8.824*	9.725*	10.726*	14.565*	14.144*	13.568*	13.538*	4.291*	5.060*	4.935*	4.707*	6.491*	6.839*	7.222*	7.582*
SBK	6.140*	6.751*	7.769	9.166*	9.156*	10.029*	11.239*	13.454*	4.181*	4.384*	4.595*	4.584*	7.714*	8.034*	8.995*	8.829*
SHP	2.498*	3.169*	3.830*	4.478*	6.012*	6.721*	6.637*	6.2178*	1.361*	1.491*	1.717*	2.312*	3.476*	3.782*	3.119*	2.860*
SSW	3.709*	4.425*	4.952*	5.269*	8.943*	8.660*	8.765*	9.294*	4.397*	5.315*	6.193*	6.031*	8.241*	8.776*	9.969*	11.163*
TBS	4.033*	5.302*	6.952*	8.327*	6.485*	7.503*	8.093*	9.113*	2.071*	3.177*	4.971*	6.340*	2.700*	3.192*	5.227*	7.555*
WBO	6.071*	7.314*	8.887*	8.910*	11.631*	9.997*	10.355*	9.955*	2.710*	3.821*	5.041*	5.120*	2.368*	4.634*	5.385*	5.864*

Note(s): The first row reports the dimension while the second row documents the embedding dimension by values of the standard deviation of the sample. * indicates significance at 1%
Source(s): Authors' estimations