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Greenhouse Gas Emissions Effect on Investor Economic Decisions: Unravelling the Nexus between Corporate Sustainability Performance and Investor Share Ownership Appetite

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ABSTRACT

The greenhouse gas emissions dilemma faced by the Republic of South Africa is undoubtedly significant as evidenced by heavy dependence on coal-fired power plants utilised for generating electricity. Statistical data depicts the country as the "culprit," positioned as the largest greenhouse gas emitter in Africa despite the backdrop of a clarion call to transition towards renewable energy. Notwithstanding that this dilemma is primarily driven by Eskom, numerous companies also contribute a fair share to this phenomenon as they attempt to balance achieving climate change mitigation targets with optimising economic value creation for investors. Inquiring the responsiveness of investors, the study aimed at determining if greenhouse gas emissions attract investor share ownership. The study employed a quantitative research design from a positivist stance to meet this objective. Accordingly, archival data were gathered from FTSE/JSE Responsible Investment Index using judgemental sampling technique. Thus, a short panel data set comprising 19 cross sections yielding 114 observations for six years were utilised for statistical panel data analysis. Adopting first differenced econometric models in data analyses, Panel Vector Autoregression Model (PVAR) for Random Effects Generalized Least Squares (GLS) regression and Random Effects Maximum Likelihood Estimator (MLE) were employed to generate the reported results. The findings indicated that investor share ownership is positively influenced by greenhouse gas emissions. As a result, the findings make notable contribution by providing new insights to investment practices in South Africa within the purview of pursuing climate change mitigation targets.

Keywords: Investors, Stakeholder, Random Effects, Sustainable Performance, Economic Decisions, Least Squares, Greenhouse Gas Emissions
JEL Classifications: Q51, O53, D63, Q56

1. INTRODUCTION

In the past decade, the importance of sustainability information and its integration into investors' investment decision making processes has grown. Greenhouse gases emissions are inherent in normal production. However, prior studies lament the negative effects emanating from poor sustainability practices by most industries. Most recently there has been growing public awareness by various lobby groups of the potential risks associated with perpetual release of greenhouse gases emissions. In this study, we focus on the FTSE/JSE Responsible Investment Index companies to establish if the link exists between greenhouse gases emissions and investors' economic decisions. Thus, we ask: Does greenhouse gases emissions influence investors' economic decisions? Researchers have conducted studies to understand the best way of integrating sustainability performance criteria in making investment decisions (Dzingai and Fakoya, 2017; Delmas et al., 2018; Lyon et al., 2018; Boze et al., 2019; Fakoya and Malatji, 2020). Moreover, several studies demonstrate that sustainability performance data may provide negative or positive effects, which are material enough to affect investors' investment decisions.

In a Russian study, Efimova (2018) conducted a multi-faceted study which investigated issues of integrating sustainability performance factors into investors' decision making processes. It was found that sustainability performance factors have a significant effect and are more relevant to institutional investors in Russia. Thus, institutional investors are compelled to find ways of incorporating sustainability performance factors into investment decision valuation models. The Russian study sheds light on the gaps that still exist in the radicalisation of Environmental, Social and Governance (ESG) practices. Efimova (2018) argues that there is still lack of standardised data, opportunity metrics, analytical tools, and ESG risk tools. Given the gaps emanating from the Russian study, it is imperative to note that other countries have attempted to intensify legislation from the reporting companies' side to enable ESG reporting compliance.

In one recent study, Saad et al. (2020) considered the role played by courts in determining the implementation of voluntary sustainability performance disclosures and reforming mandatory disclosure requirements. According to Saad et al. (2020) there seem to be a push towards making it mandatory for companies, as part of their integrated reports, to reflect expressed ESG commitments. In support of findings which show a positive effect of environmental compliance on investors' economic decisions, a German study sought to shed light on factors influencing the use of ESG data and the decision to invest in ESG compliant companies. While similar studies have used finance professionals (Green, 2019: 242), Hafenstein and Bassen's (2016) study utilised non-professional investors who consider environmental issues in their investment practices. Green's (2019) survey employed structural equation model (SEM) to show that personal orientation toward sustainability performance is a critical factor in influencing investors' decision to utilise ESG data. Moreover, the decision to invest in an ESG compliant company is greatly influenced by a variety of factors, which include willingness to forgo returns for ESG, exposure to ESG data, personal orientation, and investor's age.

Notwithstanding the attempt by previous studies to answer numerous questions on the sustainability performance phenomena, Rogers and Serafeim (2019) makes clear that more research needs to be done in this field. Furthermore, Rogers and Serafeim (2019) suggested a framework of how sustainability performance issues turn to be financially material, thereby affecting company's profitability and valuation. It is argued that understanding a process of this nature is imperative for both players driven by societal or financial motives (Cui and Docherty, 2020). According to Rogers and Serafeim (2019), there are two important groups set to benefit from the framework stated above. First, the return-first investors and companies. Second, the impact-first investors, regulators, and Non-Governmental Organisations (NGOs). The first group need this framework for making resource allocation decisions while the latter need it for designing and implementing interventions that create market-based incentives for investors and companies to align their practices with ESG outcomes (Rogers and Serafeim, 2019). While such studies (Green, 2019; Rogers and Serafeim, 2019; Saad et al., 2020) have shown international perceptions on the strides made by countries to radicalise sustainability performance practices through legislation, and how important these are to various groups, it is clear that more research still needs to be conducted in this field to fill gaps in existing literature. Hence, this paper seeks to address the following main objective: To establish if greenhouse gases emissions influence investors' economic decisions.

2. THE DECISION USEFULNESS THEORY

This study involves decision making by investors particularly when considering part ownership of a company. In the advent of sustainability accounting, decision made by investors are no longer solely based on the financial measures. Thus, emphasis on triple bottom line has taken centre stage thereby broadening the dimension of economic decision-making by investors. Besides, stakeholders in general are decision makers as they intricately have a direct or indirect interest to the business. The decision-making process of any stakeholder involves sifting for any material information, be it financial or nonfinancial. Furthermore, prior research work done in the first decade following the Wall Street Securities market crush assumed that the sole purpose of accounting is to render information to shareholders for decision making (Staubus, 1999). In the context of accounting research work done during this era, Chambers (1955) formulated the decision-usefulness theory based on stakeholders' information needs. Therefore, given the nature of this research, the results of the study were interpreted through the lenses of the decision usefulness theory.

3. RELATED LITERATURE ON INVESTORS' ECONOMIC DECISIONS FROM THE AFRICAN PERSPECTIVE

This study is done with focus on South Africa's Johannesburg Stock Exchange (JSE) to investigate the ESG phenomena in the emerging markets. This is done amidst claims that there is notable growth of integrated reporting in emerging markets given that institutional investors are beginning to consider environmental performance practices as they make investment decisions (Yamahaki and Frynas, 2016; Meziani, 2014; Hector, 2021; Macey et al., 2022; MacNeil and Esser, 2022). While studies produced in Africa are crucial, the researcher has bias towards those conducted in South Africa as they have insights relevant to this study given its context. According to Marais et al. (2022) it is more meaningful to examine ESG issues in South Africa because integrated disclosures by companies listed on the JSE are well established and institutional investors are always challenged to meet global standards in the midst of emerging market realities.

The JSE is ranked the seventeenth largest securities exchange in the world, with investor share ownership concentrated in the hands of the government and founding families of large companies (Fakoya and Malatji, 2020). Moreover, the South African government particularly holds substantial amounts of shares in large private and public companies through portfolios such as asset management of the Government Employees Pension Fund (GEPF) and Public Investment Corporation (PIC) (KPMG, 2017). Ionescu (2021) argues that GEPF puts South Africa as a country with the largest pension fund in Africa.

Furthermore, the legal system is arguably one of the best regarding investor protection (Kitsikopoulos et al., 2018). Setia et al. (2015) postulate that investors' rights and institutional structures in South Africa have proved to be strong when compared to other emerging markets. Additionally, the introduction of the King Report propelled the country forward in as far corporate governance is concerned. Consequently, South Africa is ranked among the best performers in corporate governance. This is coupled with role played by the JSE, which made it mandatory for all listed companies to make disclosures regarding ESG compliance.

Cognisant of the fact that the use of sustainability performance information by investors is still at its infancy and largely mis-understood, a number of studies have been conducted in Africa, and some with a particular focus on the South African context. Yamahaki and Frynas (2016) investigated the extent to which the legal system manipulates investors' behaviour and attitude toward environmental performance in South Africa. It was found that the impact of regulations is limited in this regard (Yamahaki and Frynas, 2016). On the contrary, regulations proved to have an impact on attitudes of investors toward integrated reporting given that it enhances investors' understanding (Yamahaki and Frynas, 2016). These studies confirm the need for researchers to explore investors' behaviour towards environmental performance issues like greenhouse gases emissions.

In support of Yamahaki and Frynas's (2016) study, Marais et al. (2022) suggest that there is limited opportunity and scope to increase the demand for sustainable investments in the country. Using a questionnaire and semi structured interviews (SSI) with selected institutional investors, the study found that there many inconsistences in how institutional investors incorporate environmental performance information in their practices (Marais et al., 2022). Such inconsistences arise against the backdrop of the growing global recognition of responsible investing. Thus, the findings highlight the need for more research to be conducted in South Africa to provide guidance and frameworks for best practices as far as integration of ESG is concerned.

3.1. Green Investors in Contemporary Times

Several studies conducted locally and, in the continent, indicate a positive association between sustainability performance and investor stake holding. Although there is limited ESG related research in South Africa in particular, previous studies have attempted to consider a composite of ESG measures to ensure that companies and investors are well equipped to consider ESG information in their practices. In one study, Johnson et al. (2019) investigated the association between ESG and Corporate Financial Performance (CFP) measures using companies listed on the JSE. While the study utilised ESG disclosure scores, a mix of accounting-based and market-based CFP measures were employed in an attempt to obtain more accurate results (Johnson et al., 2019).

Accordingly, the results demonstrated a significant positive association between the variables observed. Given the inclusivity of market-based measures in the tests conducted, conclusions reveal that investors consider ESG performance when making investment decisions (Johnson et al., 2019). However, the analysis suggested that ESG information is not homogenous across different industry sectors. Although the study provides valuable insights for this study, the study excluded finance and material sectors which are arguably the most important sectors of the economy. Moreover, data utilised in this study is outdated given that ESG reporting is progressive. This study will utilise the most recent ESG disclosure scores to achieve more accurate results.

Consistent with these findings, Atkins and Maroun (2015) also found a positive association between environmental performance issues and investors' economic decisions. Using detailed interviews and a thematic analysis of data gathered from experts in the industry, the study found that investors utilise ESG data for investment decisions (Atkins and Maroun, 2015). Institutional investors, confirmed that the new integrated reporting framework is regarded as valuable given that there is emphasis on non-financial performance measures and the inclusion of ESG metrics.

Despite insights gained from the study, given that it was the first to examine views of institutional investors in the South African context, notable gaps were observed. The study was conducted before the implementation of the International Integrated Reporting Council's (IIRC) framework adopted by preparers of IRs in South Africa. As a result, views, attitudes and the level of significance of ESG data may be different post IIRC's framework implementation.

Similarly, another study was conducted in Nigeria to demonstrate if investors can utilise environmental performance data to achieve higher returns (Salisu et al., 2022). Using an approach by Campbell and Thompson (2008), researchers found that investors utilise ESG information to exploit higher portfolio returns. Furthermore, outcomes of the study offered technical support for observing ESG related risks when making investment decisions (Salisu et al., 2022).

Furthermore, findings from a study conducted by Alhiyari and Kolsi's (2021) also found a positive relationship between environmental performance and investor stake ownership. While many studies suggest that sustainability performance practices are associated with companies' financial performance, research is still lagging in understanding securities market participants' behaviour toward ESG practices (Al Farooque et al., 2022).In this context, Alhiyari and Kolsi (2021) examined whether environmental performance provides investors with information that is value-relevant in making investment decisions.

Accordingly, the study utilised a sample of Middle East and North African (MENA) countries using a longitudinal approach for in-depth results. Findings revealed that environmental performance practices add value to earnings and book value of equity (BVE) and are positively priced by investors (Alhiyari and Kolsi, 2021). Conclusions made indicate that investors in the MENA region do incorporate environmental performance in their investment decisions. Though insightful, Alhiyari and Kolsi's (2021) study is criticised for excluding financial and banking services sectors in the sample, yet these play a vital role in the MENA capital markets. Additionally, despite retrieving ESG scores from a trusted Thomson Reuters Eikon database utilised by many researchers, there is some degree of bias given the discretionary nature of environmental performance activities. In this regard results may lack accuracy.

Furthermore, a study conducted in Zimbabwe also confirmed findings from Alhiyari and Kolsi's (2021) study, it investigated whether institutional investors in that country incorporate environmental performance practices when making investment decisions. Results revealed that the vast majority of institutional investors engage in responsible investing (Olatubosun and Nyazenga, 2017). These findings support those found in study conducted by Onichabor and Enyi (2019) who administered a survey to examine the moderating effect investment horizon on the association between environmental performance and investors' decision making in the Nigerian financial market.

Onichabor and Enyi's (2019) study proves that the investment horizon has a significant moderating effect on the association between ESG and investors' economic decisions in Nigeria. This means that expectations and prospects of an investment in the Nigerian financial market are germane to the effect of environmental performance on investors investment decisions. Studies by (Olatubosun and Nyazenga, 2017; Onichabor and Enyi, 2019) are applauded for tackling ESG imperatives in countries where little research has been conducted to investigate the environmental performance issues.

3.2. Adverse Impact of Undesirable Sustainability Performance Practices on Green Investors

Many studies conducted in Africa also holds the view that environmental performance does not influence investor share ownership. Evidence from Tunisia demonstrate that regardless of the efforts by the Tunisian government to promote environmental performance criteria since 2011, investors have not prioritised these issues when making economic decisions (Khemir, 2019). A study conducted by Khemir (2019) investigated the perception of ESG criteria by conventional investors in the emerging Tunisian financial market. The study employed SSI with financial experts and is commended for shedding light on this under-explored area in emerging countries.

Furthermore, a major finding of this study is that when it comes to investors' investment decisions, financial criteria take precedence while environmental performance is regarded as secondary. However, Khemir's (2019) study is criticised for its subjective nature with regards to the type of data collected. Thus, the study is limited to the contribution of financial experts only. Additionally, it does not pinpoint environmental performance indicators that may influence financial experts' investment decisions. The current study seeks to further reflect on these variables in the South African context.

In contrast, some studies reveal that there is a growing interest from investors to integrate ESG issues into their investment decision making processes (Jones and Slack, 2011; Earnst and Young, 2013; KPMG, 2017). A recent study conducted in South Africa, investigated the relationship between the integration of sustainability performance factors into investors' economic decisions, and assess whether investments in the JSE listed firms are held in the long-term by institutional investors (Moikwatlhai and Yasseen, 2019). In contrast to previous studies such as EY (2013) and KPMG (2017), Moikwatlhai and Yasseen's (2019) study revealed that the outcomes of Responsible Investment (RI) have not yet been fully achieved.

Furthermore, the results suggest that the commitment of institutional investors to the Code for Responsible Investing in South Africa (CRISA) and United Nations Principles for Responsible Investment (UN PRI) has not translated into shares being bought by institutional investors in the long run (Moikwatlhai and Yasseen, 2019; Owen, 2013). Moikwatlhai and Yasseen (2019) study show that there is no statistically significant relationship between explanatory ESG variables and long-term investors' share ownership.

Additionally, through a linear mixed model (LMM) approach, Moikwatlhai and Yasseen (2019) was able to show that there is a statistically insignificant relationship since the equity beta, book to price, and equity price volatility were the only statistically significant variables. Despite adding industry as a variable in the equation, this still proved to be statistically insignificant. As a result, it cemented the view that there was no statistically significant relationship between the level of long-term institutional investment and ESG scores.

Notwithstanding the relevance of this study to the current research, several criticisms levelled against it suggest a need for further scrutiny in the South African context. First, Moikwatlhai and Yasseen's (2019) study did not juxtapose the local market with other emerging countries as part of the analysis in order to generalise the findings from the study across other developing countries. Secondly, Moikwatlhai and Yasseen (2019) only focussed on investor share ownership as defined by CRISA, thereby excluding service providers of institutional investors who action investment decisions under a prescribed mandate, for example, fund managers, consultants and asset managers. Thirdly, the study had a limitation in that it does not incorporate other investment classes such as fixed income investment instruments. Fourthly, Moikwatlhai and Yasseen (2019) limited this study to variables that were tested in prior studies. More variables could be incorporated in the current study to perform cluster and factor analysis to attain more conclusive results in the South African context.

In a replica study, Fakoya and Malatji (2020) examined whether institutional investors incorporate environmental compliance issues when deciding which industry sector to consider for investments on behalf of their trustees. The study utilised South African mutual fund companies which are listed on the JSE to employ panel data analysis. The study demonstrated that an insignificant negative relationship exist between the ESG proxies and ROE (Fakoya and Malatji, 2020). These results suggest that these JSE sampled companies disregard the UN PRI guidelines, indicating that institutional investors are concerned about maximising the returns on investments without paying attention to the environmental performance issues.

As a result, the disregard for responsible investment does not promote sustainable business practices as companies are not pressured by investors' demands to improve their unsustainable business practices. If investors would advocate for sustainable business practices by considering ESG factors, companies will be forced to consider ESG issues seriously since failure to do so may lead to loss of investments. Fakoya and Malatji's (2020) study is criticised for its limited proxies, as ESG indicators could shed lighter on the investment patterns among institutional investors.

In contrast to the findings of Olatubosun and Nyazenga (2017), Chiromba (2020) contends stating that in Zimbabwe, sustainability performance have no significant influence on the investors' investment decision. Chiromba (2020) further argues that statutory frameworks used in the country are not adequate for responsible investment, as such there is great expectation that policy makers, private institutions and investors will collaborate to shape the investment framework. Such efforts will close the gap between knowledge about sustainability performance practices and investor interests.

Notwithstanding the growing calls by ESG advocacy groups on the need to integrate ESG factors when making investment decisions, responsible investment in Zimbabwe is still lagging. While Chiromba's (2020) study proves this notion, more research still needs to be done in this area. Although informative and applauded for being one of the first studies in Zimbabwe to interrogate the variables being investigated, Chiromba's (2020) study employed scanty data to perform correlational analysis, linear analysis, and ordinal regression analysis. Thus, such data may render inconclusive results and be misleading.

Drawing from the literature critically reviewed to identify the gap in research, the research hypothesis is stated as follows:

H_0: Greenhouse gases emissions does not influence investors' economic decisions.

This research study seeks to advance knowledge regarding the relationship between greenhouse gases emissions and investors' economic decisions locally, continentally, and internationally. Thus, the next section explores the methodological approach adopted by the researcher to test the hypothesis.

4. METHODOLOGICAL APPROACH AND DATA ANALYSIS

This section of the paper outlines the methodology adopted for the study. Accordingly, Meissner et al. (2011) argues that a researcher must set out the philosophical assumptions underlying a study. In this context, the researcher adopts positivism to frame the study (Morgan, 2007). This paradigm is preferred because of its association with quantitative techniques, where variables are empirically tested through observation and measurement (Crowe et al., 2011). As a philosophical stance of the natural scientist, positivism focuses on observable and measurable facts (Saunders and Lewis, 2018). The quantitative nature of the positivist paradigm therefore makes it suitable for this study. According to Groenewald (2004), quantitative research is used when researchers are interested in testing the relationship between the variables. This approach is suitable for the current study given that it employs a deductive approach to explain the relationship between two or more variables using numerical data and statistical methods (Mertler and Reinhart, 2016; Saunders and Lewis, 2018). Moreover, given the nature of the current study, the researcher adopted a multiple case study design to investigate the underlying phenomenon. A multiple case study approach allows the researcher to select a number of cases to enhance analytical generalisation and make comparisons across several cases (Crowe et al., 2011). This design is deemed a suitable fit for the current study that seeks to scrutinise the cases of companies in the FTSE/JSE Responsible Investment Index.

4.1. Population, Sampling Technique and Research Sample

The population for the current study constitute the aggregate of all the known objects, members or subjects that conform to the set of specifications (Leedy and Ormorod, 2010; Kitsikopoulos et al., 2018). The JSE introduced the Socially Responsible Index (SRI) in 2004, comprising 57 companies, following the introduction of sustainability initiatives globally and the King Code in South Africa (Greyvenstein, 2010). Companies appearing in the JSE All Share Index were reviewed annually against the ESG concerns for inclusion in the SRI. The SRI grew to 82 companies by the end of December 2014 which marked the last review under the SRI banner. However, SRI was subsequently replaced by the FTSE/JSE Responsible Investment Index (RII) which was launched in October 2015 to continually promote sustainable development and foster good corporate citizenship. Therefore, the population of this current study consist of all companies appearing on the FTSE/JSE RII from 2016 to 2021. This implies that the population will comprise of 60 companies listed on the FTSE/JSE RII as of June 28, 2021. Furthermore, Hui et al. (2011) refer to a sample is a subsection of a population chosen to participate in the study. Thus, the current study employed judgemental sampling technique. This technique is a non-probability sampling method employed when the researcher's judgement is used to select elements for the sample based on a range of premises (Etikan, 2016). The researcher collected environmental performance data of companies that have reported the environmental performance indicators consistently for a period of 6 years. Consequently, the sample comprises 19 companies drawn from the 60 FTSE/JSE SRI in the 2021 fiscal year. This represents 32% of the population, which is deemed acceptable for the study given the environmental impact and reporting practices of companies sampled purposively.

4.2. Research Data and Collection Procedure

Secondary data are data that have already been collected from other sources and are readily available for use by the researcher.

Boslaugh (2009) argues that while this data is collected for a purpose other than the research at hand, it helps the researcher to have a better understanding of a phenomena. Secondary data are suitable for its employability in exploratory, correlational, descriptive and evaluative studies (Hox and Boeije, 2004). Given the benefits of using secondary data, this study utilised panel data retrieved from the Integrated Annual Reports (IARs) of the top FTSE/JSE SRI companies. These companies were investigated for the 6 financial years from 2016 to 2021. The choice of these financial years is justifiable given that the FTSE/JSE SRI was launched in 2015. Moreover, reporting on corporates' sustainability performance only became mandatory for listed companies in 2010 (Kamala et al., 2015; JSE, 2016). Thus, the fiscal years 2016 to 2021 are considered most recent to be employable given that markets and environmental sustainability concerns have evolved sharply at global stage level calling for a wholistic ESG criterion.

Furthermore, this study employed content analysis to collect data needed to meet the objective of the study. The researcher employed this approach to sift through archival documents to identify the needed data for the phenomena being studied (Guthrie et al., 2004). Data were collected from the documents sourced and captured on Microsoft Excel spreadsheets in preparation for the data analysis process using chosen statistical software packages. Where a variable needed calculation, such calculations were done on the Excel spreadsheet. Based on the sampled companies, it was anticipated that some companies may be computing their reports using foreign currency. In such cases, the researcher converted all foreign currency to the local one for the purposes of consistency in the analysis processes. Additionally, where the variable measurement method employed by reporting companies differs, conversions were done on an Excel spreadsheet for standardisation purposes. Where the researcher encountered missing data, the interpolation (also known as adjustment) technique was employed to fill in the missing data points. Its applicability is justified as the interpolation technique is widely employed in most econometrics and statistics research (Church, 2002; Boslaugh, 2009).

4.3. Operationalisation of Main Variables for the Study

The table (Table 1) below shows how the data that relate to independent variable and control variables as extracted from the IARs and SRs for the purposes of analysis.

Table 1: Measurement of independent and control variables

Variable	Variable sub-name	Measurement method in IARs and SRs
Independent variable	Greenhouse gases emissions (GHG)	Metric tonnes of CO_2 equivalent (Mt CO_2e)
Control variables	Solvency (SOL))	Total assets to total liabilities
	Return on Shareholders' Equity (ROSE)	Net operating profit to equity
	Earnings (EnG)	Total of Net Profit after tax
	Corporate size (cSZ)	Company's total assets

Source: Author's compilation, 2024

The sustainability performance indicator presented in Table 1 is informed by the Global Reporting Initiative (GRI), Eco-Management and Audit Scheme (EMAS), and European Commission's guidelines. The reporting companies are guided by these guidelines to produce standardised reports for non-financial information. Companies presents such information in their sustainability reports, ESG reports, and or IARs. Furthermore, the table further shows how the researcher measured or proxied the control variables associated with the objective of the study. These measures are adapted from previous studies with similar objectives (Ali et al., 2019; Reverte, 2020; Veltri et al., 2020 Hartzmark and Sussman, 2017; Hawn et al., 2018; Durand et al., 2019).

4.4. Operationalisation of Dependent Variables

Investors become shareholders through buying a stake or part ownership in companies listed in the securities exchange. Traditionally, it is believed that numerous factors, other than environmental performance, influence economic decisions of these investors. However, the current study posit that share ownership may be influenced partly by such environmental performance given that reporting has evolved to incorporate ESG disclosures. Consequently, other factors that are traditionally believed to influence investors' share ownership are employed as control variables (Table 2). The table 2 depicts the dependent variable utilised in the study.

4.4. Panel Data Analysis Procedures

The study involves a balanced short panel data set of all the companies depicted in the sample. Xu et al. (2007) explains that panel data analysis techniques are useful tools for dealing with cross-section time series data. These techniques have been widely used by researchers in the field of economics (Kouki and Said, 2012). To this end, panel data analysis is preferred by most researchers when investigating numerous research questions in diverse fields of research. Furthermore, panel data analysis tools have been employed by researchers such as Arellano (2003), and Baltagi (2001). Baltagi (2001) argues through econometrics that panel data is preferred in that it supplies the researcher with highly informative data that tend to be robust in yielding more conclusive results on the phenomena being investigated. Moreover, panel data provides greater variability, less collinearity between research variables, more degrees of freedom and efficiency (Baltagi, 2001). To support this assertion, Fisher and Marshall (2009) indicates that the advancement in technology has aided panel data to be utilised in a more comprehensive manner where more econometric relationships are analysed. In addition, panel data uses both cross-sectional and times series data sets in a repetitive manner for a given number of observations (Kouki and Said, 2012). Therefore, the researcher employed panel data analysis given that the current study uses variables presented in time series cross-sectional data sets.

The study employed two powerful software packages for data analysis: STATA 18 and Eviews 13. Descriptive statistical analysis, Pearson's pairwise correlation, Panel Vector Autoregressions for Random-effects Generalized Least Squares (GLS) and Random-effects Maximum Likelihood Estimator (MLE) were mainly conducted using STATA for a modest presentation of results. To complement STATA, the researcher employed Eviews 13 to run some statistical diagnostic tests on the data.

4.4.1. Test of hypothesis
The adopted research design and methodological approach employed in this study is deemed adequate to test the null hypothesis indicated below as:

H_0: Greenhouse gases emissions does not influence investors' economic decisions.

4.4.2. The main decision rules for statistical analysis
The Table 3 is a summary of the main decision rules employed by the researcher with respect to Pearson's pairwise correlation, Hausman specification and the Breusch Pagan Lagrangian multiplier tests.

4.4.3. A priori assumptions for the study
The following assumptions apply in interpreting Pearson's pairwise correlation and Random effects coefficients produced by respective statistical estimations. Accordingly, a positive sign (+) of the coefficient confirms the existence of a relationship between the estimated variables. Conversely, a negative sign (-) of the coefficient indicates the non-existence of a relationship between the estimated variables. Most importantly, whether the effect is significant or insignificant in explaining the relationship between the concerned variables depends on the predetermined level of significance for that estimation (i.e. 10%, 5% and 1%).

4.5. Descriptive Statistics and Pearson Pairwise Correlation
Fisher and Marshall (2009) posit that in descriptive statistics, data can be organised, analysed, and presented in a meaningful manner. The current study envisaged presenting data such as mean, minimum, maximum, observations, and standard deviation in a table format. According to Adam et al. (2019: 69), descriptive statistics is a useful tool for non-parametric and parametric tests. Moreover, it is also argued that descriptive statistics is imperative in both quantitative and qualitative research, hence it should be performed to give the researcher a glimpse of the dataset utilised in the study (None and Kumar Datta, 2011; Ionescu, 2021). Furthermore, descriptive statistics is of paramount importance as it unravels normality in the distribution of the sample employed in the study and gives a clear depiction of any outliers in the dataset (Gill et al., 2008; Fisher & Marshall, 2009; Marshall and Jonker, 2011). Most importantly, normality reveal the degree of sharpness and symmetry in the dataset being examined. Farrokhi and Mahmoudi-Hamidabad (2012) indicates that descriptive statistics is also adulated in research for providing information on the measures of dispersion and central tendency. Conversely, pairwise correlation is commendable for enabling the researcher to compare and explore the relationships between variables (Agresti and Finlay, 1998). The researcher pronounces that the research data utilised in this study fulfilled all relevant statistical diagnostic tests as expatiated in the next section.

4.6. Statistical Diagnostic Tests and Panel Data Analysis Techniques
Prior to conducting the study, the researcher conducted several relevant preliminary diagnostic tests (Marshall and Jonker, 2011). This preceded the selection of the models employed in the study given that such tests renders the selection criteria. Marshall and Jonker (2011) and Getahun (2014), suggests that model estimation process commences with the panel unit root test to check if the series is stationary at level – I(0) or at first difference – I(1). In the case of stationarity at I(0) the Pooled Ordinary Least Squares (POLS) model may be employed. However, in the latter the researcher proceeds to perform the cointegration test to check if long-run relationship exists between variables. The cointegration test may reveal that variables are not cointegrated which allows the research to perform the Hausman specification test to choose between the Panel Vector Autoregression (PVAR) Model for Fixed Effects or Random Effects tests. Conversely, for variables that are cointegrated, the Panel Vector Error Correction Model (PVECM) may be adopted to enable the researcher observe short-run and long-run dynamics among the variables. Accordingly, numerous statistical diagnostic tests performed comprised panel data tests for normality, serial correlation, multicollinearity, heteroscedasticity, and stationarity.

In tandem to these tests, the researcher applied varied statistical estimations to test the proposed main hypothesis of this study. These estimations include Panel Vector Autoregression (PVAR) models for Random effects GLS regression and subsequently Random effects MLE to generate the main results of the study. The Pearson pairwise correlation matrix was computed to complement the results of the main model specified. The next section deals with model specification and its operationalisation for the purpose of statistical analysis.

4.7. Statistical Modelling of the Study
The researcher employed the techniques above in order investigate if greenhouse gases emissions influence investors' economic decisions. Getzmann et al. (2014) argue that statistical models in research can render intuitive visualisations that aid the researcher in identifying relationships between variables being studied and make predictions using such statistical models on raw data.

4.7.1. Operationalisation of the basic panel data model
The basic panel data model can be presented as shown in Equation (1) below:

$$InvST_{i,t} = \alpha + GHG_{i,t}{}'\beta + c_i + \delta_t + \varepsilon_{i,t} \quad (1)$$

Where *InvST* and *GHG* denotes the dependent variable and vector of explanatory variables for firm *i* at time (year) *t*, respectively. The time trend *t* allows for a shift of the intercept (α) over time, capturing time effects such as technology and regulation changes among others. However, if the implicit assumption of a constant rate of change is strong, a set of time dummies is introduced (δ_t), one for each time-period except reference period. The subscript ε is the error term. The component captures the variables responsible for unobserved heterogeneity (unobserved effect). It is usually a "nuisance" component of the model.

If the explanatory variables are so comprehensive that they capture all relevant attributes of i, then c_i can be dropped, and pooled ordinary least squares (OLS) can be used. However, this situation is highly unlikely. Generally, dropping c_i may lead to bias estimations resulting from missing variables problem. Thus, c_i is strongly assumed to be strictly exogenous to the conditional error term as shown in equation (2) below.

$$E\left[\varepsilon_{i,t}|GHG_{i,1}, GHG_{i,2}, \ldots, GHG_{i,T}, c_i\right] = 0, t = 1, \ldots, T \tag{2}$$

Under the strict exogeneity condition as highlighted in equation (2), equation (1) can be reproduced as follows:

$$E\left[InvST_{i,t}\varepsilon_{i,t}|GHG'_{i,t}, c_i\right] = \alpha + GHG_{i,t}'\beta + c_i + \delta_t \tag{3}$$

This implies that β' are partial effects holding c_i constant. However, to estimate β the relationship between $GHG_{i,t}$ and c_i must be clarified, giving rise to different estimators of Equation (3) such as the pooled, fixed effects, and random effects models. The pooled model's assumptions are often unrealistic, as previously mentioned. Hence, most researchers opt for either fixed or random effects model based on the results of the Hausman Test.

The fixed effects model (FEM) assumes that the unobserved effects (c_i) are correlated with the regressors (GHG'_i).

$$E\left[c_i|GHG_i\right] = g\left(GHG_i\right) = \alpha_i \tag{4}$$

Then, $$InvST_{i,t} = \alpha_i + GHG_{i,t}'\beta + \varepsilon_{i,t} \tag{5}$$

As a result, the regression line can be shifted up and down by a fixed amount of each i. Equation (5) is consistently estimated using OLS.

The random effects model (REM) assumes that the differences between cross sectional units are random, drawn from a given distribution with constant parameters. Most importantly, it assumes that that the unobserved effects (c_i) and the regressors are uncorrelated.

$$E\left[c_i|GHG_i\right] = \mu \tag{6}$$

$$InvSO_{i,t} = \mu^* + GHG'_{i,t}\beta + v_{i,t}, v_{i,t} = u_i + \varepsilon_{i,t} \tag{7}$$

The composed error term ($v_{i,t}$) introduces contemporaneous cross-correlations across the i group. While equation (7) can be consistently estimated using OLS, GLS and maximum likelihood estimator (MLE) may offer greater efficiency.

5. EMPIRICAL RESULTS, ANALYSIS AND DISCUSSIONS

5.1. Descriptive Statistics of the Panel Data

This section presents the results of the summary with respect to descriptive statistics. STATA 18 and Eviews 13 were utilised to import data from MS Excel to perform the analysis. These software packages for statistical analysis are employed by most researchers for their easy to use interface, graphics quality, command line programming interface, sophisticated data management and powerful analytic tools (Onditi, 2016). Besides, these software packages simplify statistical analysis especially for this study where panel data were used. The researcher generated the descriptive statistics summary which was later exported to MS Excel for editing. Accordingly, the researcher edited the summary statistics table by eliminating sum square deviation and other post-estimations such as the Jarque-bera and probability which were considered unfit for descriptive statistics analysis. Thus, mean, standard deviation, minimum and maximum values were presented for all composite variables employed in the study (Table 4).

Table 2: Measurement of the dependent variable

Variable	Variable sub-name	Measurement method in IARs
Dependent variable	Investors' Stake (InvST)	Number of shares traded during the fiscal year

Source: Author's compilation, 2024

Table 3: The main decision rules

Assumptions	Decision rule
Pearson pairwise correlation matrix	If P<0.05, where α= 0.05 (Significance level), then Reject the null hypothesis of 'no correlation', accept the alternative.
Hausman test for Random vs Fixed effects	If P<0.05, where α=0.05 (Significance level), then Reject the null hypothesis that "Random effects model" is consistent, accept the alternative in favour of Fixed effects.
Breusch and Pagan Lagrangian multiplier (LM) test for random effects	If P<0.05, where α=0.05 (Significance level), then Reject the null hypothesis favouring "simple ordinary least squares (OLS) regression," accept the alternative in favour of Random effects Generalised Least Squares (GLS) regression

Source: Author's compilation, 2024

Table 4 depicts positive mean values for all variables employed in the study. The minimum and maximum values assist the researcher understand how data are spread out in each variable. The range can also be calculated for each variable to check how wide the dataset is spread. Moreover, standard deviation abets the researcher in understanding how far observations in the dataset are from the mean values. Furthermore, the researcher also considered kurtosis values to understand the normality of the dataset being scrutinised. The data generated a positive kurtosis given that kurtosis values were higher than the normal distribution kurtosis of 3. This leptokurtic kurtosis suggests a peaked-curve for the given dataset with leverage (LEV) variable showing significant sharp-peakness of the curve with the kurtosis value above the mean. In conjunction with consideration of the measures of normality, skewness values assisted to understand the degree of asymmetry in the dataset. Thus, corporate size (CoSZ), greenhouse gases emissions (GHG), investors' stake (InvST) and solvency (SOL) exhibited availability of outliers. The researcher employed truncation strategies to handle such outliers prior to the commencement of statistical estimations. Table 4 depicts the summary of descriptive statistics for the panel dataset employed in the study.

In Table 4, all variables utilised in the study were presented to show measurements for dispersion and central tendency. It should be

Table 4: Summary of descriptive statistics

Variable		Mean	Std. Dev.	Min	Max	Observations
Greenhouse gas emission (GHG)	Overall	5303.973	7476.846	65.571	35500	N=114
	Between		7575.85	67.054	29727	n=19
	Within		1024.331	−203.027	11076.97	T=6
Investors' stake (InvST)	Overall	7E+08	8.19E+08	321309	3.21E+09	N=114
	Between		8.25E+08	759338.3	3.08E+09	n=19
	Within		1.44E+08	2.88E+08	1.52E+09	T=6
Earnings (EnG)	Overall	5790.132	15005.35	−91917	79021	N=114
	Between		7273.556	−4922.33	22948.67	n=19
	Within		13213.51	−81204.5	61862.46	T=6
Solvency (SOL)	Overall	0.72193	0.529764	0.15	3.79	N=114
	Between		0.386868	0.22	1.528333	n=19
	Within		0.370952	0.038597	3.630263	T=6
Corporate size (CoSZ)	Overall	4.710789	0.543494	3.69	5.68	N=114
	Between		0.549595	3.74	5.623333	n=19
	Within		0.081833	4.254123	4.939123	T=6
Return on Shareholders' Equity (ROSE)	Overall	0.867456	3.659612	0	26.7	N=114
	Between		2.887685	0.025	12.75	n=19
	Within		2.328736	−11.8825	14.81746	T=6

Source: Author's computation, 2024

noted that "*N*" represents the number of observations in the panel dataset employed in the study. On the other hand, "*n*" represents the sample i.e. the number of companies whose panel data set is being examined. Most importantly, "*T*" represents the time-period being investigated (2016 to 2021) in the study. Moreover, the standard deviation shows how dispersed the data is relative to the mean values. The mean values depict the numeric quantity that represents the centre of a collection of numbers.

5.2. Results Depicted by the Pearson's Pairwise Correlation Matrix

The pairwise correlation matrix is used to determine the strength and direction of the relationship between two variables. Notwithstanding the significance of data presented in Table 4, a pairwise correlation matrix was computed to understand how variables under study relate or depend on each other. Accordingly, data were exported from MS Excel to STATA 18 which is an advanced integrated software package used by researchers for all data science needs. This software package was preferred by the researcher for modest visualisation of pairwise correlation results. This implies that the correlation coefficient values, probability values and number of observations are clearly depicted in the correlation matrix. Moreover, STATA 18's automated reporting allows the researchers to present the pairwise correlation matrix with starred correlation coefficients where there is positive correlation which is significant at a predetermined level of significance.

Moreover, the estimated correlation coefficient of one (1), zero (0), and negative one (−1) represents a perfect positive, neutral, and perfect inverse relationship, respectively. In general, 0.5 benchmarks a strong and weak positive relationship, whereas −0.5 benchmarks a strong and weak negative relationship. Furthermore, the estimated correlation coefficients can be utilised to detect any potential multicollinearity between variables. An estimated correlation coefficient of at least 0.8 is considered an indication of the potential presence of multicollinearity between the variables (Baltagi, 2001). Table 5 reveals that there is no correlation coefficient above 0.8, indicating the absence of potential multicollinearity between the variables.

Table 5 depicts the results of the pairwise correlation analysis for all variables applied in the regression models. the relationship between investors' stake (InvST) and green gases emissions (GHG) is positive. This output is congruent with prior literature (Alhiyari and Kolsi, 2021; Johnson et al., 2019; Petelczyc, 2022; Zumente and Bistrova, 2021). Thus, investors' stake (InvST) yielded a positive correlation value of 0.089 at $P < 0.033$ when paired with the predictor greenhouse gases emissions (GHG). The corresponding P-value produced 0.033 which indicates that the null hypothesis of "no correlation" is rejected given that the P-value is far less than the stated level of significance. Although weak, this is indicative of positive correlation between the two variables tested at 0.05 level of significance.

5.3. Statistical Diagnostic Tests Conducted on Panel Dataset

The Table 6 is a summary of the preliminary tests conducted for the study as indicated the methodology section of this paper.

5.3.1. The Kao residual cointegration test

The results of Kao Residual cointegration test indicates the Augmented Dickey-Fuller approach probability values. Thus, in conjunction with the panel unit test which confirmed that key variables employed in the study are stationary at first difference, the cointegration test was performed to ascertain the long-run relationship among variables (Getahun, 2014). Getahun (2014) further argues that cointegration test must be performed using variables on the level form such that raw data of such variables is considered for this purpose. Moreover, to decide whether variables are cointegrated or not, the decision criteria stipulates that the null hypothesis is rejected for $P < 0.05$. The researcher employed Eviews 13 software to perform Kao Residual cointegration test. In all cases, cointegration test indicated that all variables of interest in this study are not cointegrated. This demonstrates that although stationery at first difference, there is no evidence of

Table 5: Pearson's pairwise correlations matrix

Variable	Greenhouse gases emissions (GHG)	Investors' stake (InvST)	Earnings (EnG)	Solvency (SOL)	Corporate size (CoSZ)	Return on Shareholders' Equity (ROSE)
Greenhouse gas emissions (GHG)	1					
Investors' Stake (InvST)	0.089	1				
Earnings (EnG)	−0.037	0.002	1			
Solvency (SOL)	0.182*	0.227**	−0.308***	1		
Corporate size (CoSZ)	0.213**	0.244***	0.194***	0.085	1	
Return on Shareholders' equity (ROSE)	−0.097	−0.039	−0.043	−0.008	−0.334***	1

*, **, and *** denote significance levels at 10%, 5%, and 1%, respectively. Source: Author's computation using STATA, 2024

Table 6: Statistical diagnostic tests for panel data

Assumptions	Test employed	Decision rule	Remark
Normality	Jarque-bera tests	Normal distribution, if P>0.05	fulfilled
Heteroscedasticity	Breusch Pagan-Godfrey heteroscedasticity test	Homoscedasticity present, if P>0.05	fulfilled
Multicollinearity	Variance Inflation Factor (VIF)	VIF values must be<10	fulfilled
Serial correlation	LaGrange Multiplier (LM) test	No serial correlation of any order, if P>0.05	fulfilled
Stationarity	Panel unit root test - "Fisher type" based on the Augmented Dickey-Fuller approach (ADF)	Non-stationary, if P<0.05	Fulfilled – I (1)
Cointegration test	Kao Residual	Not cointegrated, if P>0.05	Fulfilled

Source: Author's computation, 2024

long-run relationships among variables. Accordingly, variables for the study were selected with automatic selection for lag length. The null hypothesis of no cointegration is accepted given that the Augmented Dickey Fuller test shows P = 0.1971 which is >5% significance level. Therefore, the alternative hypothesis of cointegration is rejected indicating that there no long-run relationship among variables for this sub-objective. According to Xu et al. (2007), where cointegration tests indicates evidence of cointegration among variables, the Vector Error Correction Model (VECM) has to be adopted for further statistical analysis. However, Kaddoura and Westerlund (2023) reports that that Pooled Ordinary Least Squares Model (POLS) and Panel Vector Autoregression Model (PVAR) are common models for handling panel data where variables are not cointegrated. In tandem with the results of the cointegration test, the researcher employed the latter models to handle panel data presented for this study. Besides, Baltagi (2008) argues that these are more suitable where short run dynamics are being investigated given that this study does not render long time dimensions, rather only a 6-year period is under scrutiny.

5.3.2. The Hausman specification test

The Hausman test is frequently used to determine whether the Fixed effects or Random effects models are better suited for panel data analysis. The test allows one to determine whether the Random effects assumption (that individual-specific effects are uncorrelated with the independent variables) is valid or if Fixed effects should be used instead. If the Hausman test yields a P < 5%, the null hypothesis that the Random effects model is consistent is rejected in favour of the Fixed effects model. If the P > 5%, the null hypothesis is accepted, implying that the random effects model is more appropriate. Consequently, the results of the Hausman test conducted for the study indicated a P = 0.881 with respect to the lead variable greenhouse gases emissions. These results show that the Random effects are the appropriate estimator for all the specifications of the study. This means that the specifications for the study are estimated using Equation (7) stipulated above. In tandem to these results of the Hausman test, the study's main estimations are as expatiated in the next section.

5.4. Presentation of the Main Results

The robust preliminary statistical diagnostics were considered so that the findings presented below are sufficiently consistent to be relied on for policy development. These included, among others, heteroscedasticity and the appropriateness of the estimation technique. Moreover, statistical diagnostic analysis for cross-sectional dependency and serial correlation tests were already fulfilled albeit not prioritized given that the study has a relatively short time frame (6 years). According to Baltagi (2008), cross-sectional dependency and serial correlation tests are typically applied to macro-panels with long time dimensions i.e. at least 30 years. Moreover, the potential presence of multicollinearity, although fulfilled, is not prioritized given that the Pearson's pairwise correlation matrix presented in Table 5 also tackles this problem. Notwithstanding the Hausman test results which demonstrated Random effects as the appropriate estimation technique, the need for Random effects Generalised Least Squares regression (GLS) or simple Ordinary Least Square (OLS) regression in each specification was further verified using the Breusch and Pagan Lagrangian multiplier (LM) test for Random effects GLS regression. The null hypothesis for the LM test is that variances across firms or cross-sectional units are equal to zero. This implies no significant differences between firms, i.e. no panel effect. As a result, the LM test produced very small P-value (<5%), implying that the null hypothesis (in favour of OLS) cannot be accepted. Thus, Random effects GLS regression were conducted and presented below.

Table 7 shows that the probability of F-statistics (Prob > Chi-square), which is required to determine whether all coefficients in the model are jointly different from zero, is >5% in the GLS estimates. Thus, Table 7 depicts the F-statistics values of 0.305 for the lead variable greenhouse gases emissions (GHG). This

Table 7: Random effects GLS regression and MLE results

Dependent Variable: ln (Investors' stake ownership)		
	Using –gls- (GHG)	Using-mle- (GHG)
Constant	13.105***	16.493***
	(4.215)	(6.130)
ln (Greenhouse gases emissions)	9.304***	9.526***
	(1.327)	(1.368)
ln (Return on Shareholders Equity)	−0.0004	0.004
	(0.013)	(0.050)
ln (Earnings)	0.009	0.007
	(0.007)	(0.054)
ln (Corporate Size)	5.213*	3.020*
	(2.867)	(3.600)
ln (Solvency)	0.141	0.139
	(0.117)	(0.279)
Observations	114	114
R-Squared	0.009	
Number of firms	19	19
Prob>Chi-square	0.305	0.000
Prob>=Chi-square		0.000

* and *** denote significant levels at 10% and 1%, respectively. In parenthesis are robust standard errors when using Random-effects Generalized Least Squares (GLS) regression and standard errors derived from asymptotic theory when using Random-effects Maximum Likelihood Estimator (MLE). The former is robust to heteroscedasticity of the errors and the latter is robust to both heteroscedasticity and violations of the normality assumption. Source: Author's estimation using STATA, 2024

implies that the Generalized Least Squares (GLS) regression is not fit to estimate the objective's specification, hence the need for a more robust test. Similarly, while the R-squared statistic, which is used to assess how well the regression model explains observed data, is not critical in panel data, it is alarmingly low. Thus, Table 7, shows the R-Squared values of 0.009 for the explanatory variable. This indicates the need to test the robustness of GLS estimates with another estimation technique. As a result, the Maximum Likelihood Estimator (MLE) was employed, and the probability of the F-statistic (<5%) for the specification suggests that the data fits well in the estimator. Maximum likelihood estimation considers both regression coefficients and variance components, or Fixed- and Random-effects terms in the likelihood function.

Anderson and Hsiao (1981) demonstrate that the maximum likelihood estimators are consistent as the number of cross-sectional units approaches infinity, regardless of the assumptions about the initial condition (whether it follows Random or Fixed effects). Nonetheless, despite using different estimators, the change in magnitude of the estimated coefficient is barely noticeable while the statistical significance of the corporate size (CoSZ) variable has maintained its statistical significance at 10% for both Random-effects Generalized Least Squares (GLS) and Maximum Likelihood Estimator (MLE) outputs. Furthermore, greenhouse gases emissions (EmGHG) maintained a positive and statistically significant effect at 1% in both estimators employed for the study. Besides the stated variables yielding positive results, all other control variables (ROSE, SOL and EnG) used in the study are statistically insignificant in explaining investors' stake (InvST) except for the constant, which is positive and statistically significant at 1% across all specifications.

6. CONCLUSION

Consistent with the model specifications for the objective of the study, estimations were conducted to assess if greenhouse gases emissions affect investors' stake. The rational of this study entails that companies need to make deliberate efforts to comply with the sustainability performance standards given growing calls for integrated reporting. These integrated reports must not be window dressed, rather due diligence should be given to key sustainability variables that matter to lure potential investor support. The study adopted econometric models to conduct estimations for modest presentation of results. This followed that the study was quantitative in nature, using panel data of sampled companies that form part of the FTSE/JSE Responsible Investment Index. The research data were collected using content analysis of IARs and SRs. In tandem with the results of the robust preliminary diagnostic tests, the study employed Random effects GLS and MLE to perform the analysis. As a result, greenhouse gases emissions (GHG) produced a positive and statistically significant effect at 1% in both estimators employed for the study. This estimation was found to be congruent with Pearson's pairwise correlation matrix which indicated a positive relationship between investors' stake (InvST) and green gases emissions (GHG) (Table 5). The first finding implies that the firm's sustainability performance in terms of greenhouse gases emissions influences investors' economic decisions. This finding is in tandem with prior studies that agree with this association. For instance, Petelczyc (2022) found that investors in Poland consider sustainability performance to invest in a sustainable way.

In agreement with these findings, a positive correlation between companies' sustainability performance indices and its securities market performance was observed (Deng and Cheng, 2019). Moreover, Deng and Cheng (2019) concluded that the effect of environmental performance indices on non-State-Owned Enterprises (SOEs) is more significant than that on SOEs. Zumente and Bistrova (2021) conducted a landmark survey in 37 financial markets in the Baltic countries (Latvia, Estonia, and Lithuania) to analyse if investors in this region care about firms' sustainability performance. The survey suggest that a significant portion of participants make use of sustainability performance data when making investment decisions (Zumente and Bistrova, 2021). Moreover, Sood et al. (2022) sought to discover most prominent environmental performance criteria that may affect investors' economic decisions. The results revealed that sustainability performance influences investors' investment decisions (Sood et al., 2022). Furthermore, Kraemer-Eis et al. (2020) postulates that investors appear to apply environmental performance screening on an exclusionary basis when doing due diligence, while others explicitly target companies that do well on pre-selected ESG criteria.

Given, the results of the study that yielded positive findings, it is recommended that companies attempt to align with the common agenda of clean energy and reduction of greenhouse gases emissions to combat the climate crisis. However, the main limitation of this study revolves around the industry sectors employed which display some degree of bias given that the targeted population is the FTSE/JSE RII. Consequently. Future studies may seek to broaden the focus to interrogate companies in the mainboard if not all listed companies to generate more conclusive results for the study.

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