# Responsible investing – is it worth it? A comparison of South African and United States stock markets

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**Abstract**
In recent years, companies have been pushed towards good corporate citizenship. Consequently, responsible investment-driven capital allocation strategies have emerged as investors seek favourable sustainability exposure in their portfolios by increasingly applying non-financial factors to screen investments. However, the question of whether it is worth it in terms of risk and returns remains largely unanswered due to the mixed evidence and theoretical predictions. Accordingly, in this study, the performance of the FTSE/JSE Responsible Investment Index (RSI 113) was compared to the performance of the FTSE/JSE All Share Index (J203) in terms of returns and volatility in a GARCH framework. The comparison was extended to include the S&P 500 and S&P 500 ESG indices. The results show that there is a case to be made for responsible investment in South Africa but less so in the American market. These findings have significant implications for investors, companies and policymakers alike.

**Keywords:** ESG; Responsible Investing, GARCH; South Africa; United States

## 1. Introduction

Recent years have seen a push towards sustainable business practices and good corporate citizenship among companies. Consequently, responsible investment-driven capital allocation strategies have emerged as investors seek to invest based on the values they uphold by increasingly applying non-financial factors to identify material risks and growth opportunities (Manninen, 2017). In response, brokerage firms and mutual fund companies have started offering financial products that follow ESG criteria – a set of standards for a company's behaviour used by socially conscious investors to screen potential investments (Raghunandan and Rajgopal, 2022). The environmental criterion considers how a company safeguards the environment through its corporate policies (Yong et al., 2020). In contrast, the social criterion examines how the respective company manages relationships with employees, suppliers, customers, and the communities where it operates (Gillian et al., 2021). The governance criterion deals with a company's leadership, executive pay, audits, internal controls, and shareholder rights (Cavaco et al., 2020). A company's scores in these criteria determine its overall ESG score and attractiveness to investors seeking more sustainability exposure in their portfolios.

Portfolios that invest in companies that adhere to ESG standards will likely earn higher risk-adjusted returns because such companies enjoy reduced short-term risk due to insulation from earnings shocks linked to the internalisation of sustainability costs, reduced long-term risk due to strategic positioning and lower share volatility due to a more stable and huger long-term shareholder base (Whelan & Fink, 2022). Such companies are less likely to face litigation or incur the higher costs associated with the management and disposal of hazardous waste, labour unrest and regulatory fines – to name a few (Anderson, 2022). There is also a theoretical basis for companies with high ESG scores outperforming the market and companies with low ESG scores. The argument is that the market underreacts to ESG information as it insufficiently recognises the value effects of a positive ESG event (Hvidkjær, 2017). This is because ESG information is mostly found in the intangibles, which are typically more salient and uncertain than the tangibles that appear directly on a company's balance sheet. This leads to significant undervaluation of such companies, and an investment strategy that exploits this undervaluation can earn abnormally high returns.

Several studies have documented the benefits of ESG adherence. For instance, Margolis et al. (2009) documented a positive link between corporate social and financial performance. Endrikat et al. (2014) found a positive link between financial and environmental performance, while Friede et al. (2015) noted a non-negative relationship between ESG scores and corporate financial performance. Ashwin Kumar et al. (2016) found lower volatility and higher returns in high-ESG US companies. Kotsantonis et al. (2016) reported higher competitive advantages among high-ESG companies and higher risk-adjusted returns in portfolios with material ESG metrics relative to conventional portfolios. Verheyden et al. (2016) found that using a best-in-class ESG screening approach contributes positively to risk-adjusted returns. Portfolios show higher returns, lower risk, and no significant reduction in diversification potential despite reducing the number of companies due to such screening. Hang et al. (2018) found a link between ESG performance and firm profitability. Giese et al. (2019) showed that companies' ESG information was transmitted to their valuation through lower costs of capital, higher valuations, higher profitability, and lower exposures to tail risk.

However, some doubts have been expressed about the benefits of ESG investing. First, there is the possibility that the application of ESG analysis and screening in investment strategies may compromise the principles of sound portfolio management (Anderson, 2022). Secondly, there are claims that companies have been insincere or misleading in touting their ESG accomplishments. Greenwashing has become an ever-present risk as companies face pressure to adhere to rising ESG trends and expectations (De Silva Lokuwaduge & De Silva, 2022). Thirdly, the lack of global standards for regulating ESG investments continues to pose significant challenges in the investment industry. Without standardised and consistent disclosures across investee companies, it becomes challenging to eliminate greenwashing and address conflicting ESG priorities (Anderson, 2022). Fourthly, an issue that Clements (2021) deems to be a greater problem than greenwashing in exchange-traded funds (ETFs) is comparability. To capture ESG-directed capital, ETF issuers use disparate ESG considerations such that investors face significant information acquisition and synthesis costs and difficulty comparing products. This issue has grown as product choice has expanded.

There is also a theoretical basis for the inferior performance of high-ESG stocks and investments. Firstly, investors tend to ignore certain stocks, like low-ESG stocks, while focusing on high-ESG stocks. Hvidkjær (2017) shows that this results in undervaluation and higher returns in the former and overvaluation and subsequently lower returns in the latter. Secondly, companies shunned by investors due to low ESG scores are incentivised to practice very conservative accounting because regulators scrutinise their industries considerably. To the extent that investors do not account for this, it will lead to underreaction and subsequent high returns (Hong & Kacperczyk, 2009). Thirdly, the ESG screening of stocks can reduce diversification benefits. Diversification is maximised when there are no restrictions on the investable universe. Thus, any restrictions lead to a worse trade-off between risk and return. Fourthly, there are costs associated with ESG screening, which is an especially pertinent challenge for passive, low-cost investors. Despite Fama's (1970) efficient market hypothesis, in which he presented markets as informationally efficient and warranting a passive, low-cost investment strategy, ESG investing is more compatible with active trading (Hvidkjær, 2017).

Several empirical studies are in line with these arguments. For instance, Rathner (2013) found little evidence of outperformance in either direction between ESG and conventional funds. Revelli and Viviani (2015) reported that ESG investing was neither a weakness nor a strength compared with conventional investments. Halbritter and Dorfleitner (2015) found no significant return difference between high- and low-ESG companies. Further, their regressions revealed a significant but unexploitable influence of several ESG variables. Manninen (2017) found that responsible investing depended on asset class, the challenge in implementation and performance estimating methods. Generally, however, the funds are still focused on financial returns. Kim (2019) noted how socially responsible investing improves the financial performance of companies. However, the study also noted the opposite, concluding that ESG and conventional investments perform the same. Cornell (2021) noted that while investor preferences for highly rated ESG companies can lower the cost of capital, the returns are lower for investors. Further, to the extent that ESG is a risk factor, highly ESG-rated companies earn lower returns.

In sum, there are theoretical explanations of why high ESG investments should outperform low ESG investments. Factors such as insulation from earnings shocks, reduced risks and general underreaction to ESG information can contribute to higher risk-adjusted returns. However, there are also theoretical explanations of why high ESG investments might underperform low ESG investments, such as differential investor attention, conservative accounting, reduction of diversification benefits and the costs associated with active trading. Empirical studies also exhibit mixed results; some report a positive association between ESG efforts and corporate financial performance, while others report a negative association. Even more, some studies report no differences between the performance of ESG-driven investments and conventional investments. Yet, ESG is becoming popular by the day. This lack of consensus and the continued popularity of the concept motivated its examination from the perspective of an emerging market with subsequent comparison to a developed market. The rest of the paper is organised as follows: Section 2 describes the data and methods employed, Section 3 presents the results and analysis, and Section 4 concludes the study.

## 2. Methodology

This study compared the performance of the FTSE/JSE Responsible Investment Index ( RSI 113) to the FTSE/JSE Africa All Share Index (J203) in a GARCH framework. The RSI 113 is a market-cap weighted index which comprises all eligible companies that achieve the required minimum FTSE Russell ESG rating (JSE, 2022). On the other hand, the J203 is a market capitalisation-weighted index, constituting the top 99% of the total pre-free-float market capitalisation of all listed companies on the Johannesburg Stock Exchange (Bloomberg, 2022). The comparison was extended to include the S&P 500 ESG and the S&P 500 indices. The S&P 500 ESG index is a broad-based, market-cap-weighted index which measures the performance of securities meeting sustainability criteria. The S&P 500 index, on the other hand, tracks the stock performance of 500 large companies listed on US exchanges and covers about 80% of its market capitalisation (S&P Dow Jones Indices, 2022). The data on these indices from 2014 to 2022 was obtained from Bloomberg. Following Rupande et al. (2019) and Chipunza et al. (2020a; 2020b), the daily return, $R_t$ was calculated using $P_t$, the closing price on day t, $P_{t-1}$, the previous day's closing price, and $DY_t$ the dividend yield on day *t*, as:

$$R_t = \ln\{[P_t + (DY_t * P_t/100)]/P_{t-1}\} * 100 \quad (1)$$

The returns from Equation 1 were subsequently used in preliminary tests to select the best model. These tests include normality, autocorrelation, heteroscedasticity and ARCH-LM tests. The presence of ARCH effects in the series confirmed the appropriateness of the GARCH models for modelling conditional volatility. Accordingly, the GARCH (1,1) of Bollerslev (1986), the GJR-GARCH (1,1) of Glosten et al. (1993) and the E-GARCH (1,1) of Nelson (1991) were employed to examine the performance of the series in terms of returns and volatility. Each model's basic mean equation, similar in all specifications, was specified and estimated as in Equation 2 wherein $y_t$ is the index return, $\mu$ is the mean, $\phi$ captures the effect of past returns on current returns, $\nu$ captures the effect of past shocks on current returns, and $\delta$ is the risk premium. However, unlike the mean equation, the three models – GARCH (1.1), GJR-GARCH (1.1) and E-GARCH (1.1) – have different conditional variance equations respectively specified and estimated as in Equations 3, 4 and 5. Therein, $h_t$ is the conditional variance, $\omega$ is the intercept, $\alpha$ and $\beta$, capture the effect of shocks in volatility and past volatility on current volatility, respectively:

$$y_t = \mu + \phi y_{t-1} + \nu e_{t-1} + \delta h_{t-1} + e_t \quad (2)$$

$$h_t = \omega + \alpha e_{t-1}^2 + \beta h_{t-1} \quad (3)$$

$$h_t = \omega + \alpha e_{t-1}^2 + \beta h_{t-1} + \gamma e_{t-1}^2 d_{t-1} \quad (4)$$

$$\log(h_t) = \omega + \alpha\left[\left|\frac{e_{t-1}}{\sqrt{h_{t-1}}} - E\left(\frac{e_{t-1}}{\sqrt{h_{t-1}}}\right)\right|\right] + \gamma\frac{e_{t-1}}{\sqrt{h_{t-1}}} + \beta h_{t-1} \quad (5)$$

The GARCH (1.1) Equation 3 assumes that the response of time-varying volatility to negative and positive shocks is the same, and hence shocks are modelled symmetrically. To counter this drawback, the GJR-GARCH (1.1) model in Equation 4 accounts for asymmetries in the response of volatility to negative and positive shocks by adding a multiplicative dummy such that $\gamma$ captures the leverage effects (Shamiri & Hassan, 2007). A statistically significant and positive $\gamma$ denotes leverage effects (Brooks, 2019). However, the GJR-GARCH (1.1) may still violate the non-negativity constraints. Therefore, non-negativity conditions ($\omega > 0, \alpha > 0, \beta \geq 0$ and $\alpha + \gamma \geq 0$ ) were artificially imposed to ensure that coefficients are positive. The E-GARCH (1.1) model in Equation 5 employs logs to counter the drawback of artificially imposing non-negativity constraints. More so, like the GJR-GARCH (1.1), the E-GARCH (1.1) captures the leverage effects in stock return volatility. Therefore, in Equation 5, a statistically significant and negative $\gamma$ denotes the leverage effects. The SBICs were employed to choose the best model among the three after evaluating whether the stationarity condition ($\alpha + \beta < 1$) was met the equations for the models estimated.

There is a tendency to assume that GARCH processes are stationary even in cases where sample periods span periods of economic turmoil where structural breaks are present. This may cause problems in modelling volatility as the GARCH assumptions may not hold (Karlsson, 2016). Accordingly, structural breaks were considered in the examination of risk and returns of the four indices. This is in line with evidence of occasional discrete shifts in the conditional variance processes, which suggests structural changes on the markets (Abdennadher & Hallara, 2018).

Accordingly, using the most appropriate GARCH specification selected for each return series based on the SBIC, the multiple structural change test by Bai and Perron (1998) was used to identify the break dates in volatility and incorporate them into GARCH models. A quadratic spectral kernel-based HAC covariance estimation was specified using pre-whitened residuals to allow for serial correlation in the errors. Subsequently, the Bai-Perron (1998; 2003) test of globally optimised breaks against the null of no structural breaks was conducted. The dates and number of breakpoints were then identified based on the F-statistic.

Following the estimations and the selection of the best models for each of the four indices, the focus turned to exploring the indices' performance concerning various aspects of volatility, including volatility asymmetry, clustering, mean reversion, and the risk-return relationship. The aim was to provide insights into how the indices reacted to upward and downward price movements, their behaviour during turbulent market conditions, and whether they exhibited mean-reverting characteristics during the sample period employed. Additionally, the comparison of the performance of the indices included a thorough examination of the risk-return relationship to evaluate the performance of each index in terms of both risk and return. By considering these dimensions, the research offered a nuanced comparison of the indices and addressed the concerns of investors – the possibility that ESG investments may not be worth it and may be underperforming traditional investments. Findings from such comparisons provide valuable information for investors looking to make informed decisions by assessing the risks and returns associated with different indices.

## 3. Results and discussion

### 3.1 Return plots and descriptive statistics

As alluded to above, the comparative examination of ESG-geared and conventional investments has become increasingly important due to the recent push towards good corporate citizenship among companies and the need for responsible investment-driven capital allocation strategies among investors. Figure 1 below contains the daily return plots for the four indices examined in this study. The plots suggest that variance was not constant over time and followed an autoregressive pattern, giving rise to volatility clustering. Some periods appear riskier than others, as depicted by the higher volatility of returns. The most notable event that coincides with these riskier periods is the covid-19 pandemic. The RSI 113 index appears to exhibit higher risk than the JSE 203 index, contrary to the expectation that higher ESG exposure reduces volatility in returns as reported in the literature (Ashwin Kumar et al., 2016; Hvidkjær, 2017; Whelan & Fink, 2022). Further, South African indices also appear to exhibit higher risk than the S&P 500 and the S&P 500 ESG indices, consistent with the argument that emerging markets are riskier than the more established and developed ones. However, the plots confirm all the series' stationarity as they exhibit constant means over the sample period.

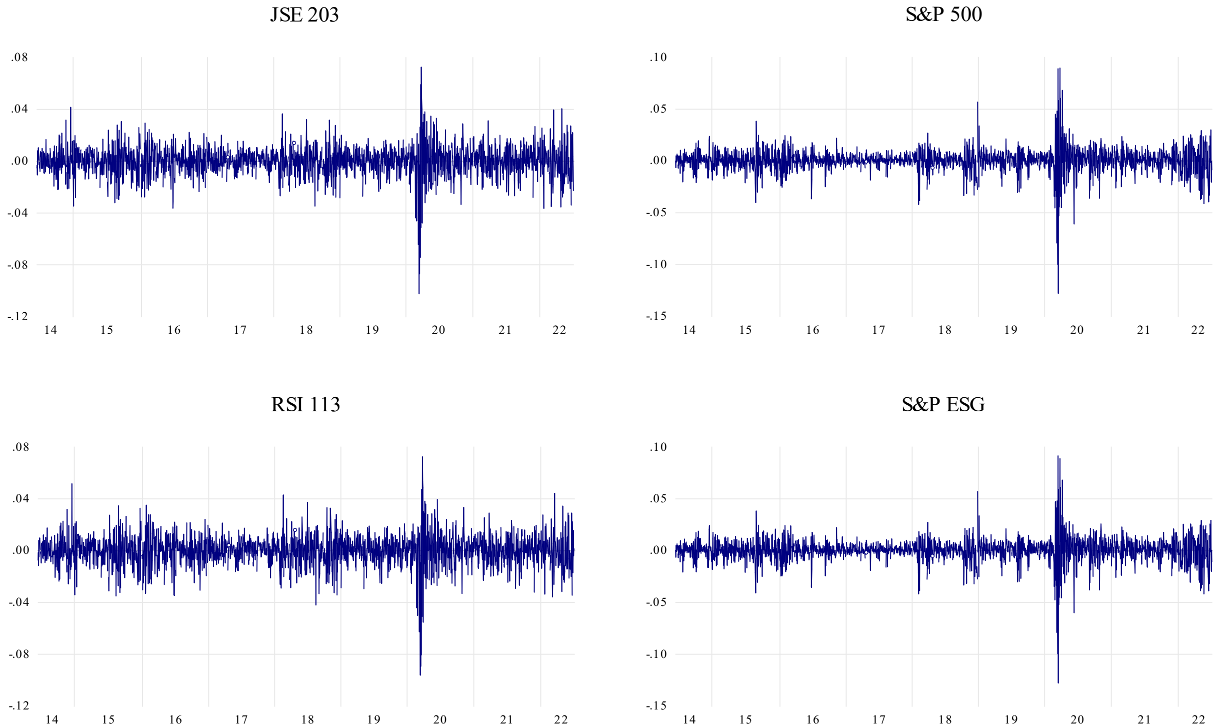


**Figure 1.** Index return plots

Table 1 below contains the descriptive statistics of the four indices. Of note, all the mean daily returns were positive, suggesting a bullish market over the sample period. However, the RSI 113 index had the lowest return (0.0092%), 0.0052% lower than the JSE 203. The RSI also exhibits a higher standard deviation (1.2310%) than the broad market index (1.1591%), suggesting higher volatility. This is consistent with the index return plots in Figure 1 above. This suggests that ESG investing is not worth it in South Africa. In terms of mean returns, the opposite is true for the S&P 500 and the S&P ESG indices; the latter exhibits a marginally higher return (0.0357%) relative to the former (0.0333%). Taken together with the statistics from the two South African indices, these statistics indicate that ESG investing benefits are market-dependent. However, the volatility on the S&P ESG index was also slightly higher (1.1637%) than on the S&P 500 index (1.1589%). Taken together with the higher standard deviation on the RSI 113 index relative to the JSE 203 index, this finding may be in line with the argument that ESG screening reduces diversification benefits due to the restrictions it places on the investable universe (Hvidkjær, 2017).

In terms of distribution, all the returns exhibit negative skewness. This indicates that more daily returns were below the mean than above. The kurtosis for all the markets was over three, revealing that the series had peaked means and fatter tails than a normal distribution. This means that there was a higher incidence of substantial deviations from the mean than a normal distribution. Consistent with these observations, the Jarque-Bera tests rejected the null hypothesis of a normal distribution for each series. This result, combined with the kurtosis statistics above three, suggests that the series are leptokurtic. As such, investors in these markets were exposed to extremely low or extremely high returns. The ADF test statistics for all the indices were significant at the 1 percent significance level. Therefore, the null hypothesis of the presence of a unit root was rejected in favour of the alternative. The KPSS test statistics for all the series were insignificant. Thus, the study failed to reject the null hypothesis of stationarity in levels. The results from the two tests consistently designate the return series as integrated of order zero. Accordingly, these markets' returns were used to estimate the GARCH models in levels as they satisfied the stationarity condition.

**Table 1.** Descriptive statistics

| Statistic | | JSE203 | RSI113 | S&P500 | S&PESG |
|---|---|---|---|---|---|
| Mean | | 0.0144% | 0.0092% | 0.0333% | 0.0357% |
| Standard Error | | 0.0261% | 0.0277% | 0.0261% | 0.0262% |
| Median | | 0.0419% | 0.0249% | 0.0598% | 0.0662% |
| Standard Deviation | | 1.1591% | 1.2310% | 1.1589% | 1.1637% |
| Kurtosis | | 7.7256 | 6.0341 | 17.6553 | 17.4766 |
| Skewness | | -0.6832 | -0.5871 | -0.9300 | -0.8929 |
| Jarque-Bera | | 5031.219*** | 3088.259*** | 25770.630*** | 25235.070*** |
| Range | | 17.4883% | 16.8341% | 21.7335% | 21.9151% |
| Minimum | | -10.2268% | -9.6014% | -12.7652% | -12.7693% |
| Maximum | | 7.2615% | 7.2327% | 8.9683% | 9.1458% |
| ADF | I | -44.8539*** | -44.6681*** | -14.4223*** | -14.4357*** |
| | I & T | -44.8429*** | -44.6568*** | -14.4186*** | -14.4325*** |
| KPSS | I | 0.0235 | 0.0178 | 0.0488 | 0.0521 |
| | I & T | 0.0194 | 0.0164 | 0.0503 | 0.0497 |
| Order of integration | | I(0) | I(0) | I(0) | I(0) |

***, ** and * denote significance at the 1%, 5% and 10% levels, respectively

### 3.2 Preliminary tests

Preliminarily, ARCH effects and autocorrelation tests were conducted on the indices, as reported in Table 2 below. Of note, the LB statistics were significant for all the indices, suggesting temporal dependencies in the first moment of the distribution of these returns. The Breusch-Godfrey serial correlation LM test confirmed the presence of serial correlation in returns since all the test statistics were significant up to lag order 36 for all the markets except for Japan. The serial correlation in the return series contrasts the assertion of informational efficiency in the EMH proposed by Fama (1970). The LB statistic for the squared returns was also statistically significant for all indices. This suggests that the series' second moments are time-varying, indicating the presence of heteroscedasticity and an autoregressive pattern in variance that gives rise to volatility clustering, as depicted in Figure 1. Engle's (1982) ARCH LM test for heteroscedasticity confirmed the presence of ARCH effects, as the LM test statistics for all indices were significant. Taken together, these results warrant the use of GARCH models as they can capture time-varying conditional volatility, which follows an autoregressive process.

**Table 2. Preliminary tests**

| | LB | $LB^2$ | Breusch-Godfrey LM | Engle ARCH LM |
|---|---|---|---|---|
| JSE203 | 0.055*** | 0.047*** | 68.80725*** | 725.1401*** |
| RSI113 | 0.046*** | 0.041*** | 58.71738*** | 669.8984*** |
| S&P500 | 0.009*** | 0.012*** | 207.5275*** | 817.9599*** |
| S&PESG | 0.006*** | 0.010*** | 209.2388*** | 809.1880*** |

***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. LB and $LB^2$ denote the Ljung-Box statistics for the returns and squared returns, respectively. All four tests were conducted using 36 lags.
*Own estimations (2022)*

Following the confirmation of the presence of ARCH effects in the series and the applicability of the GARCH models, the study employed both symmetric and asymmetric GARCH model specifications under the normal, student's t and generalised error distribution assumptions. The same GARCH models were estimated with specifications that included structural breaks. The appropriate model for each index was chosen based on the SBIC. Table 3 below shows the SBICs for each model estimated for the indices from the two stock markets. Firstly, most of the models estimated – particularly the E-GARCH based on all three distribution assumptions and the GJR-GARCH based on the student's t distribution – were explosive, so they were not considered for analysis as they could not model volatility. Secondly, except for very few cases, the models estimated without structural breaks generally minimised the SBICs relative to those estimated with structural breaks. As such, for three out of the four indices - JSE all share index, the responsible investment index and the S&P 500 index – models without structural breaks were subsequently analysed. While the GARCH model was chosen for the South African indices, the GJR-GARCH was chosen for the US indices.

**Table 3. Estimated model SBICs**

| SBIC | GARCH-M (1.1) | | | GJR-GARCH-M (1.1) | | | E-GARCH-M (1.1) | | |
|---|---|---|---|---|---|---|---|---|---|
| | Normal | T | GED | Normal | T | GED | Normal | T | GED |
| Without structural breaks | | | | | | | | | |
| JSE203 | -6.308 | **-6.330** | -6.328 | -6.336 | -6.351^ | -6.349 | -6.336 | -6.351 | -6.348 |
| RSI113 | -6.151 | **-6.176** | -6.174 | -6.180# | -6.198# | -5.553 | -6.179# | -6.196# | -6.194# |
| S&P500 | -6.675 | -6.748# | -6.740 | -6.700 | -6.775# | **-6.762** | -6.703 | -6.777# | -6.764# |
| S&PESG | -6.664 | -6.737 | -6.728 | -6.685 | -6.764# | -6.748# | -6.687 | -6.765# | -6.749# |
| With structural breaks | | | | | | | | | |
| JSE203 | -6.303 | -6.324 | -6.322 | -6.311 | -6.344# | -6.242 | -6.329# | -6.130 | -6.341# |
| RSI113 | -6.146 | -6.171 | -6.169 | -6.175# | -6.193# | -6.190# | -6.174# | -6.190# | -6.188# |
| S&P500 | -6.675 | -6.745 | -6.737 | -6.697 | -6.771# | -6.757 | -6.697 | -6.770# | -6.757# |
| S&PESG | -6.664 | -6.735 | -6.725 | -6.682 | -6.760 | **-6.743** | -6.681# | -6.758# | -6.742# |

# denotes explosive models, and ^ denotes the models that violated the non-negativity condition. The SBICs in bold font denote the chosen models that were employed in the analysis

## 3.3 Chosen models estimation outputs

### 3.3.1 Mean equation

As mentioned above, GARCH models contain the mean and the variance equations. Focusing on the former in Table 4 below, it is apparent that among all the four indices examined, only the JSE All Share index had a significant intercept, μ, implying that the models chosen performed better for the other indices relative to the JSE 203. There is evidence that the JSE 203 has a significant component of its return that is not explained by the factors in the model. This is possibly because the GJR-GARCH model that could have been more appropriate in modelling the JSE 203 returns violated the non-negativity constraints. However, the risk premium parameter, $\delta$, which captures the risk-return relationship, was positive and statistically significant for all four indices. This indicates the pricing of volatility as an increase in the conditional variance leads to an increase in the mean return (Brooks, 2019).

The risk premium was higher for the South African indices (0.2606*** and 0.2046**) than the US indices (0.1059** and 0.1115**). This is suggestive of higher risk on the South African market relative to the US market, consistent with their designation as emerging and developed markets, respectively (Muguto & Muzindutsi, 2022). Further, the higher and more significant risk premium on the JSE 203 relative to the RSI 113 suggests stronger feedback from the conditional variance to the conditional mean equation for the former than the latter. Considering that the RSI 113 had a lower mean return and higher standard deviation than the JSE 203, this is evidence of poor risk pricing in the former. The US market indices show more consistent feedback from the conditional variance to the conditional mean equation – the risk premium is higher for the S&P ESG than S&P 500, consistent with the higher mean return and standard deviation on the former than the latter.

The serial correlation parameter, $\boldsymbol{\phi}$, which captures the effect of past returns on current returns, was significant and negative for all four indices. This shows that all the indices are affected by market frictions, such as non-synchronous trading, which gives rise to autocorrelation (Hounyo, 2017). Expectantly, the South African indices exhibited higher serial correlation (-0.8944*** and -0.7365***) than the US indices (-0.4918** and -0.6175***), which is consistent with the differences in the level of efficiency hypothesised in these two markets. However, serial correlation is evidenced against the designation of the South African market as a weak form efficient market (Almudhaf & Alkulaib, 2013) but is in support of studies that designated the same market as inefficient (Morris et al., 2009; Lim, 2009; Grater & Struweg, 2015). It is also contradictory to the designation of the US market as efficient by some studies.

The contradiction between these findings and some past studies could be a result of the adaptive market efficiency reported on the South African and US markets (Lo, 2004; Obalade & Muzindutsi, 2018). The JSE 203 exhibited more serial correlation than the RSI 113, while the S&P ESG exhibited more serial correlation than the S&P 500. A similar pattern can be seen in the examination of the effect of past shocks on current returns, $\upsilon$. All indices exhibited some significant sensitivity to past shocks. This implies that past shocks could be used to explain a component of the current returns of these indices. The sensitivity was higher on the South African indices (0.9108*** and 0.7582***) than on US indices (0.4316* and 0.5641***), higher on the JSE 203 than on the RSI 113 and vice versa for the US indices. The structural break dummy, which was present only in the S&P ESG index, was significant. This highlights the methodological importance and accuracy of considering structural breaks.

### 3.3.2 Variance equation

The variance equation parameters – the ARCH and GARCH terms – for the selected models for the four indices were all statistically significant. This indicates that current volatility can be explained by volatility in the previous period and past innovations (Brooks, 2019). However, the explanatory power of volatility in the previous period (0.8579***, 0.8584***, 0.7606*** and

0.7626***) was stronger than the explanatory power of past innovations (0.1057***, 0.1039***, 0.0589*** and 0.0685***) as seen by the differences in the coefficients. Of note, the volatility of the South African indices was more sensitive to past volatility and innovations than the US indices. This is consistent with the efficiency levels suggested for these two markets and the consequent speed with which information is processed by investors (Muguto & Muzindutsi, 2022). However, there were no major differences between each pair from the same market.

The leverage parameter, as seen only in the equations for the S&P 500 and the SS&P ESG, were significant and positive. This confirms the presence of the leverage effect - as negative shocks increase volatility more than positive shocks of the same magnitude. This could be explained by the financial leverage hypothesis of Black (1976) and Christie (1982), which states that negative returns increase financial leverage, increasing stock return volatility. It is also possible that the asymmetric volatility reflects the existence of time-varying risk premiums (Mandimika & Chinzara, 2012). A third explanation is the volatility feedback effect, wherein an anticipated increase in volatility results in an increase in expected returns, which leads to a decline in the stock price (Talwar et al., 2021). This occurs because investors view volatility as a measure of risk. Therefore, if investors are assumed to be risk-averse, an increase in stock volatility will result in a decline in demand for that stock leading to a fall in price (Guiso et al., 2018).

The structural break dummy coefficient in the S&P ESG was insignificant, in contrast to the significant parameter in the mean equation of the same index. This means that only the returns were subject to structural breaks and less so the volatility. The degree of volatility persistence, as measured by $\alpha+\beta$, was higher for the JSE 203 and RSI 113 (0.9636 and 0.9623) than for the S&P 500 and S&P ESG (0.8195 and 0.8311), suggestive of more volatility clustering in the South African indices relative to the US indices. That is, current volatility shocks were more influential on volatility for many periods in the future in South Africa than in the US market (Engle & Patton, 2001). This pattern accords with the higher risk premiums noted in the mean equations above. According to Mandimika and Chinzara (2012), the volatility persistence parameter is important in determining the relationship between volatility and returns since only persistent volatility justifies changes in the risk premium.

According to Poterba and Summers (1988), a high degree of volatility persistence reveals that stock return volatility has a large effect on stock prices and that volatility mean reversion occurs slowly. The idea of mean reversion in volatility implies a normal volatility level to which volatility will eventually return after a volatility shock. As a result, even the very long-run volatility forecasts should converge to this same normal volatility level (Engle & Patton, 2001). For confirmation, the mean reversion of volatility, based on the half-life measure of Engle and Patton (2007), was also determined as $\ln(0.5)/\ln(\alpha + \beta)$. This statistic measures the time it takes for volatility to revert halfway back to its unconditional mean value after a shock (Samouilhan, 2007; Charteris et al., 2014). Expectedly, the half-life measures on the JSE 203 and the RSI 113 (18.6937 and 18.0371) were higher than those on the S&P 500 and S&P ESG (3.4821 and 3.7466).

This persistence in volatility could be mimicking the persistence in the information flow in these markets as per the mixture of distributions hypothesis (Clark, 1973; Tauchen & Pitts, 1983; Andersen, 1996). The RSI 113 performed marginally better than the JSE 203, but the pattern was reversed for the US indices. However, the stationarity condition ($\alpha + \beta < 1$ ) was met for all models. The non-negativity conditions ($\omega > 0$, $\beta > 0$, $\alpha \geq 0$ and $\beta + \gamma \geq 0$) and the diagnostic tests to check whether the chosen models were correctly specified were also satisfied. This means all the selected models for the conditional variance were admissible for all the indices. The GED parameters for the South African indices (8.1670*** and 7.6464***) and student's t parameters for the US indices (1.2774*** and 1.2856***) were also statistically significant. This indicates the appropriateness of the models employed and the distribution assumptions made in modelling the respective indices' variance.

**Table 4.** Chosen model outputs

| **Index** | **JSE203** | **RSI113** | **S&P500** | **S&PESG** |
|---|---|---|---|---|
| **Selected model** | GARCH-M | GARCH-M | GJR-GARCH-M | GJR-GARCH-M |
| | t-dist. | t-dist. | GED | GED |
| **Conditional mean equation** | | | | |
| **μ** | -0.0019** | -0.0016 | -9.85E-05 | -0.0001 |
| **δ** | 0.2606*** | 0.2046** | 0.1059** | 0.1115** |
| **ϕ** | -0.8944*** | -0.7365*** | -0.4918** | -0.6175*** |
| **υ** | 0.9108*** | 0.7582*** | 0.4316* | 0.5641*** |
| **Dummy** | | | | 0.0078** |
| **Conditional variance equation** | | | | |
| **ω** | 4.59E-06*** | 5.54E-06*** | 3.66E-06*** | 3.64E-06*** |
| **α** | 0.1057*** | 0.1039*** | 0.0589*** | 0.0685*** |
| **β** | 0.8579*** | 0.8584*** | 0.7606*** | 0.7626*** |
| **γ** | | | 0.3049*** | 0.2764*** |
| **Dummy** | | | | 6.55E-05 |
| **α + β** | 0.9636 | 0.9623 | 0.8195 | 0.8311 |
| **HL** | 18.6937 | 18.0371 | 3.4821 | 3.7466 |
| **GED/t-dist** | 8.1670*** | 7.6464*** | 1.2774*** | 1.2856*** |

***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. All mean equations were modelled as ARMA (1.1) processes.
*Own estimations (2022)*

The table below provides an overview of selected aspects examined to determine whether it is worth investing in high ESG companies in South Africa and how that compares to the US case. The four indices were ranked from the best performing to the worst based on each metric/aspect. Of the eight aspects listed in Table 5, the S&P ESG index outperformed the S&P 500 only in terms of the mean. However, considering that the S&P ESG underperformed the S&P 500 in terms of the standard deviation, the conclusion is that it might not be worth it for US investors to focus on high ESG companies as they do not seem to provide value in terms of portfolio performance. The poor performance could be linked to the shunning of low ESG firms and overvaluation of high ESG firms by investors (Hvidkjær, 2017), conservative accounting by low ESG firms (Hong & Kacperczyk, 2009) and reduction of diversification benefits due to ESG screening (Hvidkjær, 2017).

This finding directly contradicts various international studies, including those conducted in the US (Ashwin Kumar et al., 2016; Verheyden et al., 2016; Hang et al., 2018; Giese et al., 2019). Considering that most of these studies employed specific companies instead of indices, the results herein may portray a market-wide picture rather than a firm-specific one. The picture was reversed in the South African case; the RSI 113 outperformed the JSE 203 in five of the eight aspects the study focused on. This was more in line with the theoretical argument that the market underreacts to ESG information as it insufficiently recognises the value effects of a positive ESG event (Hvidkjær, 2017). The ESG information is typically more salient, intangible and uncertain than the tangibles that appear directly on a company's balance sheet. This leads to significant undervaluation of such companies, and an investment strategy that exploits this undervaluation can earn abnormally high returns.

The pattern in South Africa contradicts various international studies (Rathner, 2013; Revelli & Viviani, 2015; Halbritter & Dorfleitner, 2015; Manninen, 2017; Cornell, 2021). Yet, if the poor information processing due to the South African market's lower level of market efficiency relative to the US market is considered, the underreaction hypothesis presented by Hvidkjær (2017) becomes plausible. The latter is considered much more efficient and has a superior investor composition that often processes information more aptly. Overall, these findings suggest that whether ESG investing is worth it depends on the market. It is likely that more developed markets process information more efficiently such that they can detect any insincerity and greenwashing that has become an ever-present risk as companies face pressure to adhere to rising ESG trends and expectations (De Silva Lokuwaduge & De Silva, 2022).

**Table 5.** An overview of the findings

| Metric/Aspect | Ranking | | | |
|---|---|---|---|---|
| | 1 | 2 | 3 | 4 |
| Mean | S&P ESG | S&P 500 | JSE 203 | RSI 113 |
| Standard Deviation | S&P 500 | JSE 203 | S&P ESG | RSI 113 |
| The subjectivity of current returns to past returns | S&P 500 | S&P ESG | RSI 113 | JSE 203 |
| The subjectivity of current returns to past shocks | S&P 500 | S&P ESG | RSI 113 | JSE 203 |
| The subjectivity of volatility to past volatility | S&P 500 | S&P ESG | JSE 203 | RSI 113 |
| The subjectivity of volatility to past innovations | S&P 500 | S&P ESG | RSI 113 | JSE 203 |
| Volatility persistence | S&P 500 | S&P ESG | RSI 113 | JSE 203 |
| Volatility mean reversion | S&P 500 | S&P ESG | RSI 113 | JSE 203 |

## 4. Conclusion

In recent years, the push toward good corporate citizenship has intensified, leading to the emergence of responsible investment-driven capital allocation strategies as investors seek to gain more favourable sustainability exposure in their portfolios. Investors are increasingly applying non-financial factors – environmental, social and governance – to screen investments. However, the question of whether it is worth it in terms of risk and returns remains largely unanswered due to the mixed evidence and theoretical predictions. Accordingly, this study sought to determine whether a high-ESG index, the FTSE/JSE Responsible Investment Index (RSI 113), outperforms the market in general as proxied by the FTSE/JSE All Share Index (J203) in terms of returns and volatility in a GARCH framework. Considering that the South African market is an emerging market, the comparison was extended to include the S&P 500 and S&P 500 ESG indices from the US market, which is a developed market.

The findings show that the responsible investment index generally outperforms the broad market index in South Africa in most aspects relating to mean returns and volatility – the subjectivity of current returns to past returns, subjectivity of current returns to past shocks, the subjectivity of volatility to past innovations, volatility persistence and volatility mean reversion – but underperforms the broad market in terms of mean returns, standard deviation and subjectivity of volatility to past volatility. A holistic focus on all aspects of returns and volatility means that it may be worthwhile for investors in the South African market to explore responsible investing. The US case, however, paints a different picture - the S&P ESG index outperformed the S&P 500 only in terms of the mean and underperformed it in terms of every other metric. This suggests that it might not be worth it for US investors to focus on high ESG companies as they do not seem to provide value in terms of portfolio performance.

The inferior performance of the S&P ESG relative to the S&P 500 could be linked to how investors are paying too much attention and, consequently, overvaluing high ESG firms, the highly conservative accounting by low ESG firms that compete with high ESG firms, and the reduction of diversification benefits due to ESG screening. There could also be significant greenwashing without the actual creation of value, a factor worsened by the absence of international standards on ESG. However, the findings could portray a market-wide picture rather than a firm-specific picture, given that indices were used in the analysis. On the other hand, the superior performance of the responsible investment index to the South African broad market index suggests that the market underreacts to ESG information as it insufficiently recognises the value effects of positive ESG events. This could be due to the lower level of market efficiency relative to the US market.

Overall, there seem to be significant differences in performance between high-ESG and low-ESG companies dependent on the market under consideration. This has significant implications for investors in their choice of portfolios intending to increase returns while lowering risk. Companies will also be interested in these findings as they have implications for their decision on whether to increase their ESG efforts. In a market where such efforts are valued, high ESG companies may experience both an increase in share price and a low cost of capital. In their attempt to attract more investment into their markets, policymakers may also find these results interesting. Policies that ensure that companies engage in ESG activities may attract investors seeking to increase their sustainability exposure in their portfolios by increasingly applying non-financial factors to screen investments. Future studies should be conducted on firm-level data to see if these findings hold.

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