Environmental, Social, and Governance Factors in Emerging Markets: a Volatility Study

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Abstract:

Orientation: Asset managers constructing an emerging market portfolio of stocks should, along with more traditional risk metrics, consider ESG data in their due diligence and investment decision-making processes.

Research purpose: To determine whether a company's higher relative focus on ESG incorporation results in the observation of lower levels of share price return volatility, as predicted by EWMA and GARCH models.

Study motivation: Institutional investors wish to understand the role that ESG data plays in mitigating the risk of emerging market portfolios and whether the results necessitate the incorporation of ESG data in due diligence and investment decision-making processes.

Research approach/design and method: Categorisation of emerging market stocks using ESG scores and return volatility predicted by EWMA and GARCH models allowed for the analysis of aggregate corporate market risk. These volatilities paired with their respective annual ESG scores permitted a more company-specific view of this relationship.

Main findings: Companies with higher relative ESG Combined Scores exhibit lower levels of weekly volatility, but using annualised volatility weakens this relationship. The predictive ability of ESG scores to predict volatility is weak, and this weakens still further after the onset of crises, such as the COVID-19 global pandemic.

Practical/managerial implications: Incorporating ESG data into portfolio performance analysis could assist in mitigating corporate market risk.

Contribution/value add: Most research considers the state of ESG investing in developed markets rather than companies domiciled in emerging markets. This work could provide a more complete perspective of the state of ESG investing.

Keywords: Environmental, Social, and Governance; ESG scores; share price return volatility; emerging markets; corporate market risk.

JEL Classification: D62, G11, G12, G23, M14, Q5.

1. INTRODUCTION

There has been a considerable increase in the interest and demand for investments which exhibit characteristics of socially responsible investing. Underneath the broad umbrella term of socially responsible investing lies the aspects which a company might focus on for financial and/or ethical reasons – Environmental, Social, and Governance (ESG) factors. The availability of information surrounding this rather contentious topic has also grown. Bialkowski & Starks (2016) found that increasing investor interest of ESG issues has led to growth in the number of providers of ESG information (such as MSCI, Refinitiv and Bloomberg), growing media attention of ESG issues, as well as greater net inflows to SRI funds in comparison to conventional funds. Notably, Bialkowski & Starks (2016) further found that these greater net inflows were primarily because of nonfinancial considerations. Contrary to this finding, there are also studies which indicate a relationship between ESG considerations and positive financial implications for companies, such as a lower cost of capital (Wong *et al.*, 2021), as well as higher returns on equity (ROE) and returns on assets (ROA)(De Lucia, Pazienza & Bartlett, 2020).Further, investment professionals recognise this relationship. In a survey of 652 investment professionals, the majority (63%) that consider ESG information in their investment decisions do so because they believe that it is financially material to investment performance(Amel-Zadeh & Serafeim, 2017).

To date, little research has been conducted on whether considering ESG and its supposed implications for financial performance necessarily translates to a reduction in corporate market risk. As such, the research question that this paper

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attempts to answer is: do companies in emerging markets that place greater emphasis on ESG factors exhibit lower levels of share price volatility in comparison to their less ESG-focussed peers?

The Exponentially Weighted Moving Average (EWMA) and Generalised Autoregressive Conditional Heteroskedasticity (GARCH) volatility models are used to predict and analyse the share price return volatility over the period Jan-15 to Sep-21of a sample of 45 companies which operate in emerging markets. The volatility models use weekly share price data, and share prices are translated to be denominated in United States (US) Dollars. For the EWMA model, the weekly share price return data of the constituents are used to determine the optimal lambda (λ), the decay factor, which determines how responsive the estimate of the weekly volatility is to the most recent weekly percentage change (Hull, 2015). Further, this λ provides the respective weights to the estimate of the volatility for the previous week, as well as the most recent weekly percentage change in return. For the GARCH model, a maximum likelihood approach is used to determine the weights of the most recent weekly percentage change in return, the estimate of the volatility for the previous week, and the long-run average variance rate (Bollerslev, 1986).

The volatility levels of each company are analysed as opposed to the overall index, as it has been found that investors focus on ESG ratings and analysis at the company level rather than at the more aggregate level (sector or country) (van Duuren, Plantinga & Scholtens, 2015).The period has been selected such that the data include the periods prior to, during, and succeeding the large drawdown and excess levels of volatility caused by the COVID-19 global pandemic. This will assist in determining whether good ESG performance acted as a downside risk mitigator in a time of market crisis, adding to the existing body of literature on this topic, such as that of Schnietz & Epstein (2005) and Broadstock, Chan, Cheng & Wang (2021).

The sample of 45 companies was selected from the MSCI Emerging Markets Index, and the companies included in the sample are participants in the consumer discretionary, information technology, and financials sectors. These industries were selected to act as a screen to refine the selection of company ESG data, which were pulled from the Refinitiv Eikon database.

The bulk of the research encountered considers the state of ESG investing in Europe and the US as opposed to companies domiciled in emerging market economies. Thus, an analysis of selected constituents of the MSCI Emerging Markets Index, which are situated in varying emerging market economies across the globe, could provide a more complete perspective of the state of ESG investing.

2. LITERATURE REVIEW

2.1. Theoretical Literature Review

To further understand the role of ESG investing, it is necessary to discuss it within the context of theoretical frameworks, such as that of stakeholder theory and agency theory.

Stakeholder theory postulates that organisations should not only consider the interests of its shareholders, but also the interests of other stakeholders such as customers, suppliers, employees, and other members of society likely to be impacted by the company's operations(Freeman, 2010). This consideration is necessary if organisations are to be successful in the current and future business environment (Freeman, 2010). Freeman & Dmytriyev (2017) argue that the concepts of corporate social responsibility(CSR) and stakeholder theory are deeply connected and that they share common elements, such as their function and ability to create value.

Evidence of stakeholder theory through good management practices and its connection to ESG was provided by Lee &Isa (2020), who found that firms with good ESG practices increase performance. Other evidence of the benefits of CSR provided to stakeholders is given by Deng, Kang &Low (2013), who found that in the context of merger agreements, high CSR acquirers lead to larger increases in long-term operating performance and stock returns. This suggests that benefits exist for stakeholders when companies focus on the social aspect of ESG. ESG strengths were also found to increase firm value, but that subsequent disclosure of a firm's ESG strengths results in a decrease in value (Fatemi, Glaum & Kaiser, 2018). Fatemi, Glaum & Kaiser (2018) suggest that this decrease in firm value due to ESG disclosure could stem from the market's interpretation of this stepped-up disclosure as the firm's attempt to justify an overinvestment in ESG activities. This leads to the concept of agency theory.

Agency theory contradicts stakeholder theory, and states that if both the principal and agentare utility maximisers, an agent will not always act in the best interests of the principal (Jensen & Meckling, 1976). The relationship of agency theory with ESG has been confirmed by Brown, Helland & Smith (2006),who conclude that larger firms with larger boards give significantly more cash to charity, and that these firms are more likely to report details of their philanthropic ventures. This indicates that managers may engage in CSR to improve their reputations as opposed to maximising wealth for shareholders. Other work regarding ESG and agency theoryby Barnea &Rubin (2010) discovered a negative relation between insiders' ownership and a firm's social rating, which illustrates that agents are less inclined to spend cash on social causes when they have comparatively more ownership in the company. These results suggest that ESG spending can be detrimental to shareholders, as it is a cost to the company which might not subsequently generate value for shareholders.

The literature on agency theory and ESG is, however, contradicting, with studies such as that by Ferrell, Liang & Renneboog, (2016) concluding a positive relationship between CSR and value by using five agency proxies (cash holdings, free cash flow, capital expenditure, dividend payout ratio, and leverage). When a company has lower cash reserves, free cash flow, and capital expenditure coupled with higher payout ratios and interest payments, managers are inclined to govern the company properly and consider long-term value creation more carefully – which aligns with the notion of CSR(Ferrell, Liang & Renneboog, 2016).

Returning to literature consistent with agency theory, there does seem to be contrasting beliefs between company management and shareholders as to the value of CSR and ESG factors (Nielsen & Noergaard, 2011). This is possibly a result of barriers to using ESG data in the investment decision-making process, such as the lack of cross-company comparability and the lack of standards governing ESG reporting (Amel-Zadeh & Serafeim, 2017).Therefore, any potential financial benefits resulting from company focus on ESG dimensions might not necessarily lead to improved share price performance. To align the beliefs of company management and shareholders, Nielsen & Noergaard (2011) proposedan 'integrated decision model' whereby financial and ESG data are simultaneously considered, while still pursuing a single company objective. Nielsen & Noergaard (2011)do, however, recognise that simultaneous consideration of financial and ESG data will necessitate the development of more sophisticated methods that include more ESG data, and that it is first necessary to develop new financial analytical models before this theoretical model can be implemented. This greatly limits its practicality.

2.2. Empirical Literature Review

A considerable body of empirical literature exists which reinforces the theory that company focus on ESG factors is likely to improve financial performance and increase long-term stakeholder value. Friede, Busch & Bassen (2015) provide findings from 1816 vote-count studies, as well as a second-order meta-analysis of over 2000 empirical studies that have been released since the 1970s on the ESG-corporate financial performance (CFP) relationship. This research concludes that the business case for ESG investing is empirically well-founded, with roughly 90% of studies finding a non-negative ESG-CFP relation (Friede, Busch & Bassen, 2015).The second-order meta-analysis conducted did, however, include the analysis of the ESG-CFP relationship for non-equity related asset classes, which display a considerably higher share of positive findings compared to equities. Therefore, the non-negative ESG-CFP relation could be skewed by these findings and might not hold for the listed companies under review. Despite this potential drawback, Friede, Busch & Bassen (2015) assert that ESG outperformance opportunities exist in many areas of the market, including emerging markets, and this claim needs to be further investigated.

An empirical finding looking specifically at these supposed outperformance opportunities is that by Sherwood &Pollard (2018). The authors used seven basic tests (β; Returns; Sharpe Ratio; Sortino Ratio; Conditional VaR; Skewness; and the Ω Ratio) to measure the risk and reward trade-off of ESG integration into MSCI emerging market equities. The results revealed that the MSCI Emerging Markets ESG Indices had lower downside volatility and superior returns to the MSCI Emerging Markets indices. Thus, Sherwood &Pollard (2018) concluded that ESG investing may give institutional investors the benefits of risk diversification through allocating funds to emerging markets without exposing their portfolios to the same level of volatility, low liquidity, and lack of information often inherent to emerging market equities. Notably, the period used in this study was from Aug-07 to Dec-16, which includes the global financial crisis period of mid-2007 to early2009. However, this period is altogether different from the period chosen for this paper, and thus it is necessary to look at empirical evidence for the most recent COVID-19 global pandemic and the market volatility that it caused.

A recent study which analysed the ESG-investment performance relationship during such times of high market volatility was conducted by Demers, Hendrikse, Joos & Lev (2021). A multiple regression analysis of stock returns for the first quarter of 2020, as well as the full financial year of 2020 was undertaken. Contrary to the body of supporting literature for ESG and improved investment performance, this study concludes that ESG scores are not significantly associated with stock market performance during the market downturn caused by the global pandemic once other more traditional expected determinants of returns (such as a company's level of indebtedness, profitability, and liquidity) have been controlled for. Despite these results and a large sample size of 1652 firms, the findings are purely related to the US equity market, which does not allow for extrapolation to emerging markets.

There seems to be a gap in the current literature, as few studies have been conducted to determine the ESG-investment performance of emerging market stocks during the period of market volatility resulting from the global pandemic. The literature also appears to be conflicting, with different conclusions reached for developed and emerging markets. For example, despite the above mentioned conclusion reached by Demers, Hendrikse, Joos & Lev (2021), an event study conducted by Broadstock, Chan, Cheng &Wang (2021) dealing with the role of ESG performance during the global pandemic concluded that ESG performance is positively associated with the short-term cumulative returns for stocks of the CSI300 index,a Chinese stock market index replicating the top 300 stocks traded on the Shanghai Stock Exchange and the Shenzhen Stock Exchange. This conclusion was reached using a method similar to the method used by Demers, Hendrikse, Joos & Lev (2021) – regressing the returns on the ESG scores after controlling for leverage, book-to-market value, and firm size.

This paper contributes to the literature by considering autoregressive models to forecast the share price volatility of the chosen constituents, as opposed to multiple regression analyses, which are typically used to determine the ESG-investment or ESG-financial performance relationships. Given the excess market volatility experienced by global equity markets during the time-period under review, it is possibly more apt to use the GARCH (1,1) model to forecast the future volatility of the constituents of the chosen index, as it is likely that heteroskedasticity will be present in the sample, a violation of the underlying assumption of homoskedasticity in multiple linear regression models. Thus, the standard errors of a multiple regression analysis for this time-period might be underrepresented, which could lead to the occurrence of Type I or Type II errors during hypothesis testing. Further, the use of two volatility models as opposed toone adds credibility to the research outcomes.

Jakobsson and Lundberg (2018) explored the relationship between ESG-performance and total share price volatility using two separate panel regression models – a fixed effects model and a random effects model. Both the models have separate dependent variables, one being the Realised Volatility and the other being volatility estimated by the GARCH (1,1) model. The sample size included 481 companies taken from the S&P 500 index, and the time-period for the study was the period between 01-Jan-09 and 31-Dec-16. The regression results found that the ESG score was significantly negatively related to both the realised volatility and the GARCH (1,1) estimate of volatility, indicating that good ESG scores were capable of lowering the total volatility of shares (Jakobs son & Lundberg, 2018). A potential drawback of the paper is that the time-period under consideration does not include any large exogenous shocks to the global economy.

3. METHOD

3.1. Refinitiv ESG Scores Methodology

Refinitiv offers one of the most comprehensive ESG databases (Refinitiv, 2021) in the financial industry, with ratings which cover over seventy percent of global market capitalisation (Refinitiv, 2021). Refinitiv's ESG scores (ESG pillar score, ESG controversies score, and ESG combined score) provide analysts with an indication of a company's relative ESG performance, and biases such as industry materiality and company size are factored into the score generation process (Refinitiv, 2021).

Refinitiv uses a fully automated, data-driven model which captures and calculates over 500 company-level ESG measures, of which a subset of 186 measures of the most material and comparable per industry drive the overall company assessment and scoring process (Refinitiv, 2021). The data account for both qualitative and quantitative information which is made publicly available by companies. Qualitative considerations are factored into the model using Boolean values, which are either 1 or 0 depending on whether the answer to a specific question is "Yes" or "No". Each datum has a polarity which indicates whether the answer "Yes" or "No" is positive or negative (Refinitiv, 2021).Numerical data points account for the quantitative information made publicly available by a company, and these data points are relative percentile rankings (Refinitiv, 2021). The polarity concept is also applied to the numerical data points, indicating whether a higher value is positive or negative (Refinitiv, 2021).

These ESG measures are then grouped into ten main categories, including emissions, human rights, CSR strategy, amongst others (Refinitiv, 2021).To ensure comparability across sectors, Refinitiv uses a 'materiality matrix', which considers how material the categories are to each industry. The category weights vary per industry for the environmental and social pillars but remain fixed for the corporate governance category (Refinitiv, 2021).Overall ESG scores are then aggregated using the category weights determined by the materiality matrix (Refinitiv, 2021). The ESG pillar score is calculated as the relative sum of the category weights after rolling up the category scores into the environmental, social, and corporate governance pillars (Refinitiv, 2021).

An ESG Controversies (ESGC) score is also calculated based on 23 ESG controversy topics, and this score discounts the ESG pillar score based on publications of news controversies which materially impact companies, to arrive at the overall ESG score for a company (Refinitiv, 2021). The company size bias is accounted for in the ESGC score by adjusting for the fact that companies with larger market capitalisations attract more media attention (Refinitiv, 2021). This is achieved using severity weights.

3.2. Sample Selection

The sample was selected by considering which companies were constituents of the MSCI Emerging Markets Indexat the end of the last complete annum (31-Dec-20). At the time of writing, this date is the last time that Refinitiv Eikon published the ESG scores of the companies which form part of the sample. This was done by obtaining constituent information of the iShares MSCI Emerging Markets ETF (BlackRock, 2021), as constituent information could not be accessed from the Refinitiv Eikon or Bloomberg databases due to license restrictions. Fortunately, the iShares MSCI Emerging Markets ETF observed a tracking error of only 0.87% (Morningstar Direct, 2021) over the past five-year period, and the holdings of the ETF therefore do not materially differ from that of the index.

The index constituents were then screened to only consider companies which operate in the consumer discretionary and information technology sectors. Given data constraints, the financials industry was subsequently included as another of the screening industries. This worked out favourably, as companies which operated in the financial sector tended to have uniform ESG score grades, improving the accuracy of any statements regarding inter-category differences in volatility. Further, these industries were selected because they were the largest according to company market capitalisation, and together constituted over 50% of the index as at 31-Dec-20.

After the screening of constituents according to industry, company ESG score grades were collected using the Refinitiv Eikon database (Refinitiv, 2021). The companies were categorised into various ESG ratings categories, 'Category A', 'Category B', Category C' and 'Category D'. For a constituent to be placed into one of the respective categories, the company had to exhibit an applicable annual, alphanumerical ESG combined score grade on at least four of seven occasions. For example, if a company exhibited an annual ESG combined score grade of A-, A or A+ for four out of the seven years, that company would be placed into Category A.In total, there are 14 companies in Category A, 15 companies in Category B, 12 companies in Category C, and four companies in Category D. Thus, there are a combined 45 companies in the sample.

The reasons for having merely four companies in Category D is that generally, companies did not exhibit such poor ESG performance over time. Also, companies which did consistently exhibit poor ESG performance often did not have seven annual ESG combined score grades, making them ineligible to be included in the sample given the period selected for this paper.

3.3. Volatility Models

Exponentially Weighted Moving Average

The Exponentially Weighted Moving Average (EWMA) model for forecasting share price return variance is a method which was first developed through a partnership between J.P. Morgan and Reuters. This model forecasts share price return variance by accounting for what the model predicted share price return variance to be the preceding week, as well as factoring in the most recent weekly percentage change in share price. The weightings of these elements are determined by λ, the optimal decay factor.

The EWMA model is considered an improvement to the volatility model which assumes equal and fixed weights of all share price return deviations from the mean, a model known as the Simple Moving Average (SMA) (Risk Metrics, 1996). The EWMA model improves upon the SMA model by considering the weights applied to the return observations, and thus determines the effective amount of data used in estimating volatility (Risk Metrics, 1996). In this way, the value obtained for the optimal λdetermines the responsiveness of the weekly volatility estimate to the most recent weekly percentage change (Hull, 2015).

The equation for forecasting weekly share return volatility using the EWMA model is (Hull, 2015):

$$\sigma_n^2 = \lambda \cdot \sigma_n^2 + (1-\lambda) \cdot u_n^2$$

where:

λ is the decay factor, which is a constant such that $0 < \lambda < 1$; and σ_n is the estimate of the volatility for week n, calculated from σ_{n-1} (the estimate of the volatility for week n - 1 made at the end of week n - 2) and u_{n-1} (the most recent weekly percentage change in return).

Ten of the 45companies in the sample were used to determine the optimal λ. The ten companies were selected to be representative across categories (namely three category A companies, three category B companies, two category C companies, and two category D companies). Each weekly company return series has an optimal decay factor that minimises the root mean square error (RMSE) of the variance forecast. An optimal decay factor of $\lambda = 0.943$ was found.

Generalised Autoregressive Conditional Heteroskedasticity

A concern regarding the RMSE methodology is that in a non-linear and highly heteroskedastic environment, this measure could prove to be unreliable (Andersen, Bollerslev & Lange, 1999).

Thus, to achieve more robust results in this paper, the GARCH (1,1) model was used to predict share price return volatility for the sample of 45 companies. Developed by Bollerslev (1986) and built upon the foundation of the ARCH model (Engle, 1982), the GARCH (1,1) model accounts for volatility clustering, which is a phenomenon frequently observed by financial return series (Engle, 1982; Ding, Granger and Engle, 1993). The model also accounts for the long memory property of stock market returns (Ding, Granger &Engle, 1993).This is achieved by factoring in the long-run average variance rate of a time-series. Thus, GARCH treats volatility as a time-dependent and persistent process (RiskMetrics, 1996), unlike volatility models which assume independently distributed log price changes.

The formula for forecasting weekly share price return volatility using the GARCH(1,1) model is (Hull, 2015):

$$\alpha_n^2 = \omega + \alpha \cdot \mu_{n*1}^2 + \beta \cdot \sigma_{n-1}^2$$

where:

$\omega = \gamma \cdot V_L$, where γ is the weighting assigned to the long-run average variance rate (V_L) α is the weighting assigned to u_{n-1}^2, the most recent weekly percentagechange, and β is the weighting assigned to σ_{n-1}^2, the estimate of the volatility for week n - 1 made at the endof week n - 2.

The maximum likelihood method is used to determine the weightings of the various factors built into the GARCH (1,1) model. The maximum likelihood approach involves choosing values for the parameters that maximise the chance of the data occurring (Hull, 2015).Determining these parameters is an iterative process (Bollerslev, 1986): each share possesses its own unique set of parameters using maximum log likelihoods.

3.4. Pre-Estimation Test and Hypotheses

χ^2 Goodness of Fit

To determine whether the Levine Test or F-test would be most suitable for testing whether differences exist between the variances of the average weekly share price return distributions of the four categories, it was first necessary to conduct χ^2 goodness of fit tests to see whether the underlying distributions of the share prices are normal or non-normal.

The null and alternate hypotheses were thus:

H_0: The distribution of the share price returns is normal.

H_A: The distribution of the share price returns is non-normal.

Because 16 of the 45 share price return distributions are normal, tests were conducted for differences in the variance of average weekly share price returns of the categories using both the Levine and F-test.

Hypotheses

An analysis of variance (ANOVA) test was undertaken to determine whether there were differences in the mean average weekly share price volatilities of the categories as predicted by the EWMA and GARCH models. The null and alternate hypotheses for the ANOVA tests are:

$H_{01}: \mu_1 = \mu_2 = \mu_3 = \mu_4$, i.e., there are no differences in the means of the average weekly share price volatilities of the four categories, as predicted by the EWMA model.

$H_{A1}: \mu_1 \neq \mu_2 \neq \mu_3 \neq \mu_4$, i.e., there are differences in the means of the average weekly share price volatilities of the four categories, as predicted by the EWMA model.

$H_{02}: \mu_1 = \mu_2 = \mu_3 = \mu_4$, i.e., there are no differences in the means of the average weekly share price volatilities of the four categories, as predicted by the GARCH model.

$H_{A2}: \mu_1 \neq \mu_2 \neq \mu_3 \neq \mu_4$ i.e., there are differences in the means of the average weekly share price volatilities of the four categories, as predicted by the GARCH model.

F-Tests were conducted to determine whether the variance of the average weekly share price returns differed between the four categories. Null and alternate hypotheses are thus stated as follows:

$H_{03}: \sigma_1^2 = \sigma_2^2 = \sigma_3^2 = \sigma_4^2$, i.e., there are no differences in the variance of the average weekly share price returns of the four categories.

$H_{A3}: \sigma_1^2 \neq \sigma_2^2 \neq \sigma_3^2 \neq \sigma_4^2$, i.e., there are differences in the variance of the average weekly share price returns of the four categories.

Similarly, the Levine Test was conducted to determine whether there were differences in the variances between the weekly share price return distributions of the four categories. This test is conducted for all four of the categories at once, and not on a more individual basis such as the F-test. The hypotheses for the Levine test are as follows:

$H_{04}: \sigma_1^2 = \sigma_2^2 = \sigma_3^2 = \sigma_4^2$, i.e., there are no differences in the variance of the average weekly share price returns of the four categories.

$H_{A4}: \sigma_1^2 \neq \sigma_2^2 \neq \sigma_3^2 \neq \sigma_4^2$, i.e., there are differences in the variance of the average weekly share price returns of the four categories.

4. ANALYSIS AND RESULTS

4.1. Descriptive statistics

Company ESG Scores

The mean ESG Combined Score of Category A as shown in Table **1** is 79.74. The distribution of scores in Category A is significantly negatively skewed, with a median ESG Combined Score value of 80.59.This Category A distribution also has the lowest standard deviation of the four categories of 7.66%. The range for the Category A ESG Combined Scores of 39.16is the lowest range of the four categories, indicating a low level of relative dispersion.

The mean ESG Combined Score of Category B is 59.03.Category B has the lowest mean ESG Controversies Score between the categories of 88.75. This result is, however, skewed by Samsung Electronics Co. Ltd., which observed ESG Controversies Scores of between 5 and 50 for the seven annual scores obtained.

Category B has the second lowest ESG Combined Score standard deviation of 10.86%, as well as the second lowest range of 52.26. Thus, this ESG Combined Score distribution has a low relative dispersion.

A mean ESG Combined Score of 41.05 was achieved by the companies in Category C. The ESG Combined Score observations of category C companies are relatively further away from the mean, as evidenced by the highest standard deviation of 12.20%.Category C also has the largest range, indicating that some category C companies achieved scores which had highly different alphanumerical ESG Combined Scores to C-, C, or C+.

16.34 is the mean ESG Combined Score of category D companies. Category D companies observed the highest ESG Controversies score between the four categories, which is a surprising result given the companies' poor ESG performance. It is possible, however, that this result is skewed by the relatively low number of annual ESG Controversies observations of 28.

The range of 48.86 for category D observations indicates that the annual alphanumerical ESG Combined Scores of the companies within this category are relatively uniform in comparison to Category B and Category C observations.

Company Share Price Volatility

The means of the average weekly share price volatilities predicted by the EWMA model increase from 4.5% for the companies in category A to 4.93% for the companies in category B, and then to 5.59% for the companies in category C (Table 2). Thus, means of the predicted weekly volatilities do increase as the ESG scores of the companies in the respective categories worsen. This trend is not observed between category C and category D, with the means of the average weekly share price volatilities decreasing from 5.59% to 5.19%. This mean for category D is, however, still higher than both the means for category A and B.

Table 1. ESG Score Summary Statistics. Source: Refinitiv Eikon (2021).

		ESG Score	ESG Combined Score	ESG Controversies Score
A Category	Mean	81.35	79.74	94.76
	Median	81.49	80.59	100
	Standard Deviation	0.0634	0.0766	0.1551
	Sample Variance	40.17	58.69	240.47
	Kurtosis	-0.38	1.82	12.55
	Skewness	-0.31	-1.04	-3.56
	Range	26.26	39.16	75.61

	Minimum	65.88	52.77	24.39
	Maximum	92.14	91.93	100
	Count	98	98	98
B Category	Mean	61.73	59.03	88.75
	Median	61.96	57.98	100
	Standard Deviation	0.1286	0.1086	0.2353
	Sample Variance	165.38	118.03	553.65
	Kurtosis	0.31	-0.07	4.87
	Skewness	0.04	-0.4	-2.36
	Range	65.6	52.26	95
	Minimum	27.98	27.98	5
	Maximum	93.59	80.24	100
	Count	112	112	112
C Category	Mean	42.23	41.05	94.76
	Median	39.85	39.85	100
	Standard Deviation	0.1371	0.122	0.1836
	Sample Variance	188.05	148.89	337
	Kurtosis	0.99	1.43	13.32
	Skewness	0.9	0.84	-3.75
	Range	71.8	71.31	95.45
	Minimum	8.24	8.24	4.55
	Maximum	80.04	79.55	100
	Count	91	91	91
D Category	Mean	16.42	16.34	97.3
	Median	13.08	13.08	100
	Standard Deviation	0.1178	0.117	0.1428
	Sample Variance	138.69	136.84	203.88
	Kurtosis	2.61	2.79	28
	Skewness	1.63	1.66	-5.29
	Range	48.86	48.86	75.56
	Minimum	4.66	4.66	24.44
	Maximum	53.53	53.53	100
	Count	28	28	28

The standard deviations of the average weekly share price volatilities for categories C and D (1.00% and 0.92% respectively) exceed that of categories A and B (0.90%), indicating that categories C and D have predicted weekly share price volatility observations which are relatively further away from the mean than categories A and B.

The ranges for categories C and D of 5.41% and 4.47% respectively are also higher than that of categories A and B, which have ranges of 3.46% and 3.45% respectively. Thus, the weekly share price volatility distributions of categories C and D are more dispersed relative to categories A and D.

Only category C observes excess levels of kurtosis, indicating that all three of the other distributions do not observe extreme values. Further, all four of the categories are positively skewed, indicating that the mean values of the average

Table 2. EWMA Predicted Volatility Summary Statistics. Source: Author Calculations.

	A- to A+	B- to B+	C- to C+	D- to D+
Mean	4.50%	4.93%	5.59%	5.19%
Median	4.15%	4.73%	5.47%	5.21%
Standard Deviation	0.90%	0.90%	1.00%	0.92%
Sample Variance	8.05E-05	8.03E-05	1.00E-04	8.51E-05
Kurtosis	-0.01	-0.91	0.37	-0.54
Skewness	1.00	0.47	0.54	0.18
Range	3.46%	3.45%	5.41%	4.47%
Minimum	3.47%	3.42%	3.02%	3.03%
Maximum	6.92%	6.87%	8.43%	7.50%
Count	346	346	346	346

Table 3. GARCH Predicted Volatility Summary Statistics. Source: Author Calculations.

	A- to A+	B- to B+	C- to C+	D- to D+
Mean	4.75%	5.37%	5.87%	5.56%
Median	4.52%	5.18%	5.68%	5.47%
Standard Deviation	0.79%	0.70%	0.87%	0.69%
Sample Variance	6.29E-05	4.96E-05	7.65E-05	4.70E-05
Kurtosis	5.64	3.12	7.14	0.60
Skewness	1.99	1.42	2.11	0.57
Range	5.65%	5.38%	6.96%	4.22%
Minimum	3.64%	3.59%	3.61%	3.40%
Maximum	9.29%	8.97%	10.57%	7.62%
Count	345	345	345	345

weekly share price volatilities are greater than their respective median values.

The pattern of the mean average weekly share price volatilities predicted by the GARCH model (and presented in Table **3**) is largely the same as that of the EWMA distributions. That is, the mean increases from 4.75% (category A) to 5.37% (category B), and then further increases to 5.87% (category C) before decreasing to 5.56% (category D). Thus, it can again be said that the average weekly volatilities predicted by the GARCH model increase as the ESG scores of companies worsen.

The standard deviations of the average weekly share price volatility of categories A and C (0.79% and 0.87% respectively) are higher than those of categories B and D (0.70% and 0.69% respectively). Thus, categories A and C have predicted average weekly share price volatility observations which are relatively further away from the mean than categories B and D. This is different from the result obtained for the standard deviations of the average weekly share price volatility distributions predicted by the EWMA model.

The ranges of category A and C of 5.65% and 6.96% respectively indicate that the distributions of these two categories are relatively more dispersed than those of categories B and D, which have ranges of 5.38% and 4.22% respectively.

All four of the average weekly share price volatility distributions observe excess levels of kurtosis, and therefore contain extreme values. This was not the case for the distributions of the EWMA model barring that of category C. This could be a result of the GARCH model's tendency to predict volatilities which cluster (Engle, 1982 and Ding, Granger &Engle, 1993) over certain periods, causing extreme observations to persist after the market decline caused by the global pandemic. Further, the distributions predicted by the GARCH model are significantly positively skewed.

4.2. Analysis of Variance (ANOVA) Test

Table **4** below provides the results of the single factor ANOVA test for the average weekly share price volatility predicted by both the EWMA and the GARCH model.

Table 4. ANOVA Test Output. Source: Author Calculations.

Source of Variation	SS	df	MS	F statistic	F critical	p-value
Between Groups	0.02	3	0.01	83.95	2.61	6.81E-50****
Within Groups	0.12	1380	0.00			
Total	0.14	1383				
Single Factor ANOVA for Volatility Predicted by GARCH Model						
Source of Variation	**SS**	**df**	**MS**	**F statistic**	**F critical**	**p-value**
Between Groups	0.02	3	0.01	129.12	2.61	1.07E-73****
Within Groups	0.08	1376	0.00			
Total	0.10	1379				

The single factor ANOVA test for the volatility predicted by the EWMA model indicates thatthe between-treatments variation (SS = 0.02; Table **4** above), which measures the proximity of the sample means to each other, is large. Due to this large value (usually denoted as SST), the F statistic is substantially larger than the F critical value. Therefore, the null hypothesis H_{01} is rejected, and it is concluded that there are indeed statistically significant differences in the means of the average weekly share price volatilities of the four categories (p-value < 0.0001), as predicted by the EWMA model.

Likewise, in the single factor ANOVA test for the volatility predicted by the GARCH model, a large between-treatments variation is observed, resulting in a F statistic value which exceeds that of the Fcritical value. The null hypothesis H_{02} is rejected, and it is concluded that there are statistically significant differences in the means of the average weekly share price volatilities of the four categories (p-value<0.0001), as predicted by the GARCH model.

These results coupled with the means above indicate that on aggregate, companies which exhibit higher ESG Combined Scores observe lower levels of weekly share price volatility. This reinforces the inverse ESG score-share price return volatility relationship discovered by Jakobsson & Lundberg (2018).

4.3. F-tests and Levine Test

F-Tests

There is no significant difference between categories A and B, as well as categories C and D ($p > 0.05$; Table **5**).We thus fail to reject the null hypothesis H_{03} in this instance, and conclude that there is no statistically significant difference in the variance of the average weekly share price returns between categories A and B, nor between categories C and D.

Given the results in Table **5**, H_{03} is rejected as there is a significant difference in the variance of the average weekly share price returns between categories B and C ($p < 0.05$); categories A and C ($p < 0.001$); categories B and D ($p < 0.001$); as well as between categories A and D ($p < 0.0001$).

Thus, on aggregate, as the ESG Combined Scores of companies improve, the share price returnsare relatively less dispersed around their means. Further, as the ESG score discrepancy widens between categories (for example, the discrepancy between the ESG scores of categories A and D is wider than that of categories B and C), the assertion that there are differences in the variance of the average weekly share price returns between the categories can be made with a higher level of confidence.

Table 5. F-test Results (two-Sample for Variances): *n* = 345. Source: Author Calculations.

Category	$\bar{x}$	σ^2	F Value	F critical value (1 tail)	P Value (1 tail)
A- to A+	0.31%	0.07%			
B- to B+	0.33%	0.08%	0.88	0.84	0.11
B- to B+	0.33%	0.08%			
C- to C+	0.41%	0.10%	0.79	0.84	0.012*
C- to C+	0.41%	0.10%			
D- to D+	0.19%	0.12%	0.86	0.84	0.09
A- to A+	0.31%	0.07%			
C- to C+	0.41%	0.10%	0.69	0.84	0.0003***
B- to B+	0.33%	0.08%			
D- to D+	0.19%	0.12%	0.68	0.84	0.0002***
A- to A+	0.31%	0.07%			
D- to D+	0.19%	0.12%	0.6	0.84	0.0000****

Levine Tests

The Levine test further reinforces the fact that there are statistically significant differences in the variance of the average weekly share price returns between categories. The $p < 0.0001$ in Table **6** is statistically significant, and thus H_{04} is rejected, and it is again concluded that there are differences in the variance of the average weekly share price returns between the categories.

4.4. ESG Combined Scores and Annualised Volatility

To display the relationship between ESG Combined Scores and share price return volatility as predicted by the EWMA and GARCH models at a company-specific level as opposed

Table 6. Levine Test Results. Source: Author Calculations.

Source of Variation	SS	df	MS	F statistic	F critical	P-value
Between Groups	0.01	3	0.0032	7.54	2.61	0.0001***
Within Groups	0.59	1380	0.0004			
Total	0.60	1383				

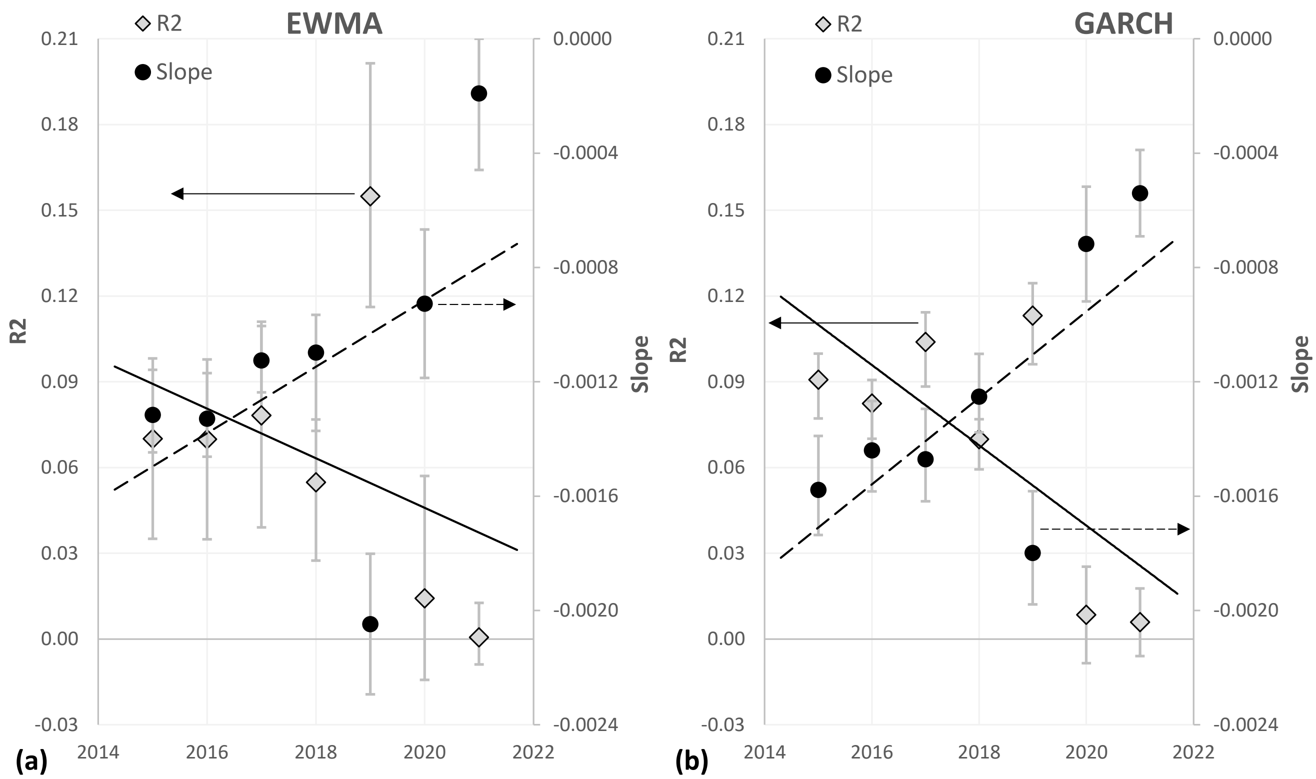

Fig. (1a). Regression analysis of ESG Combined Scores and EWMA annualised volatilities and (**b**) regression analysis of ESG Combined Scores and GARCH annualised volatilities.
Source: Refinitiv Eikon (2021) and author calculations.

to the aggregated results the weekly share price volatilities were annualised and coupled with their respective ESG Combined Scores. To analyse the predictive ability of the ESG Combined Scores, a time lag was used such that, for example, the annual ESG Combined Score of 2014 was coupled with the annualised volatility of 2015.

Fig. (**1a**) shows the annualised volatilities predicted by the EWMA model as the variable dependent on the ESG Combined Scores (the independent variable).

Note that in all seven years considered, the linear trendline is downward sloping. This shows that as the ESG Combined Scores of companies improve, annualised volatility as predicted by the EWMA model decreases. This adds to the aggregated results of the ANOVA test. The negative gradients of -0.0009 and -0.0003 for the years 2020 and 2021 respectively are, however, flatter than the negative gradients observed in the years 2015 to 2019, which range from -0.0011 to -0.0021. Thus, for the year 2020, as the ESG Combined Scores of companies improve, the annualised volatility predicted by the EWMA model decreases less so than for the years 2015 to 2019. This can be compared with thefindings of Demers, Hendrikse, Joos & Lev (2021), that ESG did not protect stocks from the market downturn caused by the global pandemic. The observation that the 2020 annualised volatility decreases to a lesser extent as the ESG Combined Score improves is even more pronounced in 2021, indicating that the inverse ESG Combined Score-predicted volatility relationship has diminished since 2020.

Further, whilst the negative slope of the trend lines reinforce the findings that there are statistically significant differences in the mean average weekly volatilities between Categories, it is important to note that the R^2 values of the linear regressions, which range between 0.15% and 15.49%, indicate that the ESG Combined Scores explain little of the percentage variance in the annualised volatilities. Therefore, there is a weak relationship between the variables, and this relationship weakens significantly in 2020 and 2021. This indicates that companies with relatively higher ESG Combined Scores can attain higher annualised volatility as predicted by the EWMA model.

The results obtained in Fig. (**1b**) for the annualised volatilities predicted by the GARCH model as the variable dependent on the ESG Combined Scores (the independent variable)are largely the same. Again, the linear trendlines are downward sloping in all seven of the years, and trendline gradients range between -0.0013 and -0.0018 between 2015 to 2019 before flattening out to -0.0007 in both 2020 and 2021. Annualised volatility predicted by the GARCH model thus decreases as the ESG Combined Scores of the companies improve, but this trend is again less pronounced in 2020 and 2021. This once more adds to the findings of Demers, Hendrikse, Joos & Lev (2021), and shows that the inverse ESG Combined Score-predicted volatility relationship has diminished since 2020.

Although the R^2 values in Fig. (**1b**) are higher than those in Fig. (**1a**) barring years 2019 and 2020, these values, which range between 0.85% and 11.32%, still indicate that the ESG Combined Scores explain little of the percentage variance in the annualised volatilities. This is again particularly true for 2020 and 2021. This indicates that companies with relatively higher ESG Combined Scores can observe higher annualised volatilities as predicted by the GARCH model.

5. CONCLUSION

The objective of this paper was to determine whether greater company focus on ESG implementation results in the observation of lower levels of share price return volatility. This objective was different to the objectives of standard work, which tested relationships between ESG performance and financial performance (Friede, Busch & Bassen, 2015; De Lucia, Pazienza & Bartlett, 2020; Wong *et al.*, 2021).

Set in the context of emerging markets, the sample used consisted of 45 companies which were constituents of the MSCI Emerging Markets Index. This focus on emerging markets adds to what is a small body of existing literature, given that most empirical results regarding company ESG incorporation and its effectsare primarily concerned with companies domiciled in the US and Europe.

Statistically significant differences in the means of the average weekly share price volatilities between the categories as predicted by both the EWMA and GARCH models exist. Further, the means increased between category A, B and C before reducing slightly for category D. This was true for the means of the weekly share price return volatilities predicted by both models. Thus, on aggregate, companies which exhibited higher ESG Combined Scores observed lower levels of weekly share price volatility, reinforcing the inverse ESG score-share price return volatility relationship discovered by Jakobs son & Lundberg (2018).

Further, statistically significant differences exist between the variances of the average weekly share price returns of all the categories barring between categories A and B, as well as between categories C and D. Thus, for the remaining categories it can be said that, on aggregate, as the ESG Combined Scores of companies improved, the share price returns were relatively less dispersed around their means.

Annualising weekly volatilities and pairing them with their respective ESG Combined Scores resulted in downward sloping trendlines, adding to the premise that companies which exhibit high ESG Combined Scores observe lower volatilities. However, the negative slope of the trend line for 2020 is less steep than those of the years 2015 to 2019, reinforcing the work of Demers, Hendrikse, Joos & Lev (2021) regarding the inability of ESG to mitigate downside risk resulting from the global pandemic. This flattening of slope is also true for 2021, indicating that the inverse relationship between ESG Combined Scores and volatility has deteriorated since 2020.

These results support the notion that ESG investing may give institutional investors the benefits of risk diversification without exposing their portfolios to the same level of volatility often inherent to emerging market equities (Sherwood &Pollard, 2018).Thus, the results suggest that ESG score data should be incorporated in some way into the due diligence and investment decision-making processes of institutional investors looking to establish an emerging market portfolio of stocks. The ‘integrated decision model’ proposed by Nielsen & Noergaard (2011),whereby financial and ESG data are simultaneously considered, could be adopted by institutional investors once it has undergone further development. Institutional investors looking to add holdings to a pre-existing emerging market portfolio will however need to individually analyse the volatility data specific to those stocks, as the ability of the Refinitiv ESG Combined Scores to predict share price return volatility for individual companies is weak.

A notable limitation of this paper is the discrepancy between the frequency of observations for the two data sets used. The ESG scores calculated by Refinitiv are done so on an annual basis only, whereas the predicted share price return volatility observations provided by the EWMA and GARCH models were made weekly. Although these volatilities were annualised, this discrepancy cannot be ignored.

Another concern is that the sample size used for this research is relatively small given that the MSCI Emerging Market index had over 1000 constituents on 31-Dec-20. This small sample size was necessitated by data constraints, which included an incomplete number of annual ESG observations provided by Refinitiv, as well as the fact that company ESG scores often change dramatically, disallowing the categorisation of some companies.

Further research should continue to probe the relationship between company ESG data and corporate market risk. It should be determined whether this relationship holds on a larger scale, by including more emerging market companies in the sample used. Another beneficial progression in the research and application of ESG data would be the development of new models, such as the ‘integrated decision model’ suggested by Nielsen & Noergaard (2011). Such a model would allow for the inclusion of ESG data in the investment decision-making processes of institutional investors, allowing for the incorporation of ESG data alongside financial data to mitigate risk.

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