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Return and Volatility Properties Comparison of High-ESG Rating and Low-ESG Rating Exchange-traded Funds (ETFs)

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ABSTRACT

This study compares return and volatility performance of exchange-traded funds (ETFs) with high-ESG (Environment, Social, and Governance) rating vs. low-ESG rating. The paper also examines time-series data predictability by identifying their positive dependence and volatility asymmetry properties, and examines the performance of two combinations of short-memory models i.e., autoregressive moving average and exponential generalized autoregressive conditional heteroskedasticity (ARMA-EGARCH); autoregressive moving average and asymmetric power autoregressive conditional heteroskedasticity (ARMA-APARCH) and two long-memory models, autoregressive moving average and fractionally integrated exponential generalized autoregressive conditional heteroskedasticity (ARFIMA-FIGARCH); and autoregressive fractionally-integrated moving average and asymmetric power autoregressive conditional heteroskedasticity (ARFIMA-APARCH). The study found that low-ESG rating ETFs on average have slightly significant higher returns and also lower volatility compared to their high-ESG rating counterparts. Evidence of asymmetric volatility properties are also present on both high-ESG and low-ESG rating ETFs returns. The study also observed that for both high-ESG and low-ESG rating ETFs denote a stationarity, but non-invertible process in their returns. Results can provide fresh understanding in the topic of leverage effects and volatility that can open future research channels to academicians.

KEYWORDS

High-ESG and low-ESG rating ETFs; volatility clustering; asymmetric volatility

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1. Introduction

Socially-responsible investing (SRI) can help investors achieve goals that go beyond financial gains. The old notion that investors should always be on achieving the best possible returns are no longer viable, because more and more investors also want to invest in companies and channels that have a positive impact on the environment and society. Investments in ESG (environment, social, and governance) funds have strong demands from investors, and have already found their way into mainstream investing. Those investors truly supporting SRIs, which pertains to investments in enterprises that act in accordance to developing ways to uplift the level of corporate governance and transparency, improving the conditions of community, and saving the environment. Aslan et al. (2021) proved this claim by showing that SRIs are an ideal substitute for the good overall performance of business organizations experiencing positive returns.

ESG investing is a strategy that channels money to enterprises and investment channels that meet stringent ESG standards. This type of investing quantifies and evaluates investment portfolios and companies in terms of their sustainable goals and actions particularly in treating their internal and external stakeholders in a responsible manner. Investment managers build their entire selection and research process to ensure that the business organizations in which they are planning invest in operate to these standards and also incorporate ESG criteria into their project selection in differing degrees.

Investing in the best ESG investment channels like mutual funds, index funds, and the growing popularity of ETFs can help SRI-conscious investors support responsible corporate behavior without sacrificing return performance. Unlike traditional mutual funds, shares of ETFs trade throughout the day on a securities exchange at prices established by the demand of the market. Albuquerque et al. (2018) found that high ESG firms experience lesser price elastic demand resulting in a lower systematic risk. This was further verified by Zhang et al. (2021) when the authors explored whether the high or low ESG rating of business organizations is related to the level of its implied risk. The authors found that their findings are consistent with previous studies suggesting that the ESG rating of a firm is indeed related to some financial risk. A more recent study by Kammoun and Tandja (2023) revealed that mutual funds with lower ESG commitment is associated with higher performance during normal periods but leads to lower performance during recessions or bear markets.

Investors considering ESG ETFs should examine each SRI closely to better suit their investing needs. ETFdb.com, the database that this study used features a number of screening tools, and particularly rates ETFs from high- to low-ESG ratings. This paper is interested in comparing the higher-ranking ESG ETFs and the lower-ranking ESG ETFs. Husted and Salazar (2006) documented the benefits of patronizing ethical businesses, which explained that more economic output and social impact will be achieved by investing in socially responsible companies. The paper of Bag and Mohanty (2021) found that ESG performance disclosures and stock returns in emerging markets have a positive impact on stock performance. In a related study, Kempf and Osthoff (2007) also found that investing in businesses with CSR activities lead to higher than the average annual returns of the S&P 500 since inception.

This paper provides further evidence regarding the return and volatility characteristics of High-ESG rating and Low-ESG rating ETFs through their asymmetric volatility and long-memory properties. The asymmetric volatility characteristics of a time-series data and describes the negative correlation between returns and volatility changes. This explains why negative shocks are often followed by higher market fluctuations than positive shocks or the so-called leverage effects. On the other hand, positive dependence in distant time-series observations or the so-called long-memory process detects the existence of a persistent temporal dependence among distant financial time-series data, which implies that both returns and volatility can be forecasted. These data characteristics have been seen in CSR indices by Liu et al. (2014), and in stock returns by Mabrouk and Aloui (2010); and Tan and Khan, (2010). However, as far as the author's knowledge is concerned there are no extensive literature comparing the asymmetric volatility and predictability characteristics of higher-ranking ESG ETFs and the lower-ranking ESG ETFs.

The research is motivated by the increasing interest of the investing public in SRIs and companies with high ESG initiatives; and the growing application of fractionally-integrated (FI) long-memory models in financial time-series data and being compared to short-memory models. This study is also motivated by the shortage in the literature of applying FI models on ESG-related investments. The paper contributes by comparing two combinations of methodologies; namely, the short-memory autoregressive moving average and exponential generalized autoregressive conditional heteroskedasticity (ARMA-EGARCH); autoregressive moving average and asymmetric power autoregressive conditional heteroskedasticity (ARMA-APARCH) and two long-memory models, autoregressive moving average and fractionally integrated exponential generalized autoregressive conditional heteroskedasticity (ARFIMA-FIGARCH); and autoregressive fractionally-integrated moving average and asymmetric power autoregressive conditional heteroskedasticity (ARFIMA-APARCH) models in examining long-term positive dependence and volatility asymmetry returns and volatility of High-ESG rating and Low-ESG rating ETFs. In relation to the motivation and contributions, this research has four main objectives:

a) identify which group between High-ESG rating and Low-ESG rating ETFs has higher returns and steadier stock price volatility;

b) identify which type of models (i.e., short- and long-memory models) using lagged returns are better to characterize future values of data samples;

c) examine the existence of the leverage effects and volatility asymmetry phenomena in

the time-series of High-ESG rating and Low-ESG rating ETFs;

d) find out presence of positive long-term dependence, and examine the dual long-memory process in the stock returns and volatilities of study ETFs.

Many fund managers are incorporating SRI selection and ESG methodology into specific ethical or socially conscious strategies, but a more sustainable effort is to establish their investment selection processes from the ground up. Portfolio managers that look for SRIs and consider ESG criteria are better equipped to operate in a sustainable manner and manage risk in the future. Thus, they are attractive investments in their own right.

The study is structured as follows: Section 2 presents the literature review; Section 3 details the data and methodology of ARMA-EGARCH, ARMA-APARCH; and ARMA-FIEGARCH, ARFIMA-FIAPARCH models; Section 4 presents the empirical results; and Section 5 presents the conclusions and limitations of the paper.

2. Literature Review

2.1. ESG and Related Studies

ESG factors have garnered increasing attention in investment circles due to their potential to influence financial performance and contribute to sustainable development. This literature review synthesizes a range of studies to provide a comprehensive understanding of the relationship between ESG factors and investment performance across various asset classes and markets.

Liu et al. (2014) employ asymmetric power models to analyze the relationship between Thomson Reuters CSR indices and major stock market indices, highlighting the susceptibility of CSR indices to economic shocks and their influence on stock market returns and volatility. This study sets the stage for subsequent research by demonstrating the interconnectedness of ESG factors with broader market dynamics.

Studies advocating for ethical investments, such as Bercicci et al. (2001), emphasize the positive relationship between SRIs and firm performance, and found that firms with high ESG performance experience positive returns, while Aslan et al. (2021) document a significantly lower likelihood of corporate credit default for businesses with strong ESG performance. O'Rourke (2003) and Reenebog et al. (2008) further support these findings by demonstrating the outperformance of ethical mutual funds and SRI funds across different regions.

Despite the positive outlook on ethical investments, challenges and contradictions exist within the literature. Hayat and Kraeussl (2011) observe underperformance of Islamic equity funds during the financial crisis of 2008, suggesting that certain ethical investment strategies may be more vulnerable to market downturns. Similarly, Reenebog et al. (2008) find that SRI funds in specific markets, such as Ireland, Sweden, France, and Japan, perform below conventional local market portfolios. Bauer et al. (2006) caution against excessive screening fees impacting the returns of SRI and ESG funds, highlighting the importance of cost considerations in ethical investing.

Several studies provide nuanced insights and neutral findings regarding the relationship between ESG factors and investment performance. Kreander et al. (2005) find no significant differences in return performances between European ethical and non-ethical mutual funds, suggesting that ethical considerations may not always translate into superior financial returns. Similarly, Bauer et al. (2005) discover no significant differences in risk-adjusted returns among ethical and high-ESG funds compared to conventional funds in advanced countries like the UK, US, and Germany. These findings underscore the complexity of evaluating the financial implications of ESG integration in investment strategies.

Recent empirical studies shed further light on the relationship between ESG factors and investment performance across different asset classes and markets. Xiong (2021) examines the impact of ESG risk on US stocks and finds that stocks with lower ESG risk ratings outperform those with higher ratings, particularly during crises such as the COVID-19 pandemic. Kammoun and Tandja (2023) analyze the performance of infrastructure mutual funds and reveal that lower ESG commitment is associated with higher performance during normal periods but leads to lower performance during recessions or bear markets. Bag and Mohanty (2021) investigate the impact of ESG factors on emerging market stock returns and highlight the significance of governance and environmental aspects in influencing stock performance.

Rompotis (2023) raises concerns about the "greenwashing" tactics employed by some ESG exchange-traded funds (ETFs), noting a high correlation of these ETFs with the S&P 500 Index and significant investments in companies with high ESG risk. This highlights the need for transparency and accountability in ESG investing practices to ensure alignment with stated environmental and social objectives.

While existing literature has extensively explored the impact of ESG factors on investment performance, there remains a gap in understanding the specific characteristics and dynamics of ESG-rated ETFs. Particularly, there is limited research on the comparative analysis of High-ESG rating and Low-ESG rating ETFs in terms of their returns, volatility, and underlying market dynamics. Additionally, there is a lack of comprehensive studies utilizing both short- and long-memory models to characterize the future values of data samples derived from these ETFs. Furthermore, the literature has not adequately addressed the presence of leverage effects and volatility asymmetry phenomena in the time-series of High-ESG rating and Low-ESG rating ETFs. Lastly, the exploration of long-term dependence and dual long-memory processes in the stock returns and volatilities of study ETFs remains underexplored.

2.2. Study Direction and Hypotheses

2.2.1. High-ESG rating and Low-ESG rating ETFs has higher returns and steadier stock price volatility

- Null Hypothesis (H0): There is no significant difference in returns between High-ESG rating and Low-ESG rating ETFs.
- Alternative Hypothesis (H1): High-ESG rating ETFs exhibit higher returns compared to Low-ESG rating ETFs.
- Null Hypothesis (H0): There is no significant difference in stock price volatility between High-ESG rating and Low-ESG rating ETFs.

- Alternative Hypothesis (H1): High-ESG rating ETFs demonstrate steadier stock price volatility compared to Low-ESG rating ETFs.

2.2.2. Short- and long-memory models and the use of lagged returns

- Null Hypothesis (H0): Short-memory models using lagged returns are equally effective as long-memory models in characterizing future values of data samples.
- Alternative Hypothesis (H1): Long-memory models using lagged returns are more effective than short-memory models in characterizing future values of data samples.

2.2.3. Leverage effects and volatility asymmetry phenomena in High-ESG rating and Low-ESG rating ETFs

- Null Hypothesis (H0): There is no existence of leverage effects and volatility asymmetry in the time-series of both High-ESG rating and Low-ESG rating ETFs.
- Alternative Hypothesis (H1): Leverage effects and volatility asymmetry are present in the time-series of both High-ESG rating and Low-ESG rating ETFs.

2.2.4. Positive long-term dependence and dual long-memory process in the stock returns and volatilities of ESG ETFs

- Null Hypothesis (H0): There is no presence of positive long-term dependence in the stock returns and volatilities of study ETFs.
- Alternative Hypothesis (H1): Positive long-term dependence exists in the stock returns and volatilities of study ETFs, indicating a dual long-memory process.

3. The Australian ETF Landscape

The series of high-ESG and low-ESG rating ETFs returns were calculated as $y_t = 100(log\, p_t - log\, p_{t-1})$, where$p_t$denotes the price at time$t$. The financial time-series data were modeled by the short- and long-memory FI processes and are explained below.

3.1. Short- and long- memory processes in the conditional mean

3.1.1**.** The ARMA Model

Box and Jenkins (1970) formulated the time-series methodologies ARMA models to capture short-range correlations, where the predictors are lagged observations represented by the AR function, while on the other hand the previous residual errors are captured by the MA process. The basic ARMA (r, s) model can be expressed as follows:

$$y_t = \varphi_1 y_{t-1} + \cdots + \varphi_r y_{t-r} + \varepsilon_t + \varphi_1 \varepsilon_{t-1} + \cdots + \theta_s \varepsilon_{t-s} \quad (1)$$

and the general ARMA (r,s) can be shown below:

$$y_t = \varphi_0 + \sum_{i=1}^{r} \varphi_i y_{t-1} + \varepsilon_t + \sum_{j=1}^{s} \varphi_j\, \varepsilon_{j-1} \quad (2)$$

where r represents the order of the AR(r), φ_i denotes the parameter, s stands for the order of the MA(s), $\theta_j$represents the parameter andε_t denotes the normally and identically distributed noise. ARMA models are flexible and are able to describe the serial dependencies of time-series using the number of parameters of the AR and MA components.

3.1.2. The ARFIMA Model

Granger and Joyeux (1980) and Hosking (1981) originated the ARFIMA model and captures display long-range correlations, which often the result of fluctuations in time-series data over time. The ARFIMA models consider the FI process $I(d)$ in the conditional mean, and allows the difference parameter to be a non-integer. The polynominals indicating the ARFIMA (r,d,s) model can be expressed as follows:

$$\varphi(L)(1-L)^d(yt-\mu)=\theta(L)\varepsilon_t \tag{2}$$

The fractional differencing operator $(1-L)_d$denotes a notation for the infinite polynominal shown below:

$$(1-L)^d=\sum_{i=0}^{\infty}\frac{\Gamma(i-d)}{\Gamma(i+1)\Gamma(-d)}L^i=\sum_{i=0}^{\infty}\pi_i(d)L^i \tag{2}$$

where$\pi_i(z)\equiv\Gamma(i-d)/\Gamma(i+1)\Gamma(-d)$ and Γ^i represent the standard gamma function. When the difference parameter is within$-0.5<d<0.5$, the process of the ARFIMA models is stationary where the influence of shocks to ε_t decays at a gradual rate to zero. If d = 0, the process denotes a short-memory and the outcome of shocks decays geometrically. When d = 1, the process denotes the presence of a unit root. For 0 < d < 0.5, the process denotes a long-memory or positive dependence among distant observations. If -0.5 < d < 0, the process is anti-persistent and has the presence of intermediate memory. When $d\geq 0.5$, the process shows non-stationarity, while $d\leq -0.5$ means that the data time-series cannot be represented by any AR model even though it is stationary, however it is a non-invertible process.

3.2. Short and long-memory models in the conditional variance

3.2.1. The EGARCH Model

Nelson (1991) formulated the EGARCH model was suggested by where the conditional variance may be written as follows:

$$ln\,\sigma_t^2=\alpha_0+\sum_{i=1}^{q}\alpha_i s(z_{t-1})+\sum_{j=1}^{p}\beta_j\,ln(\,\sigma_{t-j}^2) \tag{5}$$

where zt = εt / σt represents the normalized residuals series. The function s(.) can be specified as:

$$s(z_t)=\delta_1 z_t+\delta_2\{|z_t|-E(|z_t|)\} \tag{6}$$

where $\delta_1$and $z_t$adds the effect of the sign of ε_t whereas $\delta_2\{|z_t|-E(|z_t|)\}$adds its magnitude effect. For the normal distribution, $E(|z_t|)=\sqrt{\frac{2}{\pi}}$, the asymmetric nature of the returns can be illustrated by the nonzero value of the coefficient δ_1, while a positive value of $\delta_1$specifies a leverage effect. Furthermore, external unexpected shocks will have a stronger influence on the predicted volatility than TARCH or GJR.

3.2.2. The APARCH Model

Ding et al., (1993) created the APARCH model that includes a power term that magnifies the outliers in the time-series and can also model periods of relative tranquility and volatility in the parameters. The APARCH model rather than imposing a structure on the data estimates the optimal power term. The APARCH (p,q) model can be expressed as follows:

$$\sigma_t^{\delta} = \alpha_0 + \sum_{i=1}^{q} \alpha_i \left(|\varepsilon_{t-i}| - \gamma_i \varepsilon_{t-i}\right)^{\delta} + \sum_{j=1}^{p} \beta_j \sigma_{t-1}^{\delta}$$

whereα_0> 0, δ ≥ 0,β_j ≥ 0,α_i≥ 0 and -1 <γ_i< 1.

The APARCH model is adaptive in changing the exponent δ with the asymmetry coefficient γ_i , which represents for the leverage effect. The APARCH model can be lowered to the simpler ARCH model when δ = 2, γ_i= 0 (i = 1,. . . ,p) and β_j= 0 (j = 1,. . . ,p); and GARCH model when δ = 2 andγ_i= 0 (i = 1,. . . ,p).

3.2.3**.** The FIEGARCH Models

Bollerslev and Mikkelsen (1996) created the FIEGARCH model to offer new computation features over its short-memory counterpart. The model can be extended to account for long-memory through the factorization of the autoregressive polynomial $[1 - \beta(L)] = \varphi(L)(1-L)^d$ where all the roots of $\varphi(z) = 0$ lie outside the unit circle.

The FIEGARCH (p, d, q) is can be expressed as follows:

$$ln(\sigma_t^2) = \omega + \varphi(L)^{-1}(1-L)^{-d}[1+\alpha(L)]s(z_{t-1}) \quad (7)$$

Where d denotes the fractional integration parameter, and denotes the exponential model parameter. When 0 <d< 1 the FIEGARCH model has a long-memory process.

3.2.4**.** The FIAPARCH Model

Tse (1998) created the FIAPARCH model and accounts for persistent dependence in distant observations through the factorization of the AR polynomial $[1 - \beta(L)] = \varphi(L)(1-L)^d$ where all the roots of$\varphi(z) = 0$ is assumed to lie outside the unit circle. The FI model is another expansion of the long-memory models, which make its short-memory counterpart, the APARCH process as the foundation. The FIAPARCH (p, d, q) model can be represented as:

$$\sigma_t^{\delta} = \omega + \text{Ơ}\{1 - [1-\beta(L)]^{-1}\varphi(L)(1-L)^d\}(|\varepsilon_t| - \gamma\varepsilon_t)^{\delta} \quad (8)$$

Where d represents the fractional integration parameter, and gamma (γ) denotes the asymmetry model parameter. When 0 <d< 1 the FIAPARCH model has a long-memory process. The model can identify the relative power of negative shocks more than positive shocks' impact on volatility when γ > 0. The FIAPARCH process can be also lowered to the FIGARCH model if γ = 0 and δ = 2.

Research data utilizing daily closing prices of High-ESG rating and Low-ESG rating ETFs were extracted from Yahoo! Finance website from March 3, 2020 to September 27, 2021. The study chose these ETFs based on the ranking provided by ETFdb.com. The website has an ETF screener tool that ranks ETFs with high and low ESG scores, which measures the ability of the ETF's underlying holdings to achieve key medium- to long-term risks and opportunities arising from ESG factors. A high ESG score signifies strong environmental, social, and governance practices within the companies included in the ETF. The thirteen (13) high-ESG rating ETFs have a 10 ESG scores, while the low-ESG rating ETFs have 3 and lower ESG scores. The decision to include only ETFs with a score of 10 was made to ensure a clear distinction between high and low ESG scores, thereby facilitating a meaningful comparison in our analysis. Furthermore, only actively-traded ETFs were selected to guarantee a better time-series data with the absence of zero trading volumes, which negatively affects the ETF's returns and volatility and in turn the modeling of the financial time-series data.

4. Empirical Results

4.1. Statistics of High-ESG rating and Low-ESG rating ETFs

Table 1 shows the average returns high-ESG rating and low-ESG rating ETFs under study. From the high-ESG rating group, all ETFs experienced positive average returns, while VanEck Semiconductor ETF (SMH ETF) experienced the highest average return of 17.5%, and the second highest volatility of 6.28 variance, Franklin FTSE Australia (FLAU ETF) experienced the highest variance of 6.32. This return and volatility outcome for SMH ETF conforms to the Modern Portfolio Theory of Markowitz (1952), stating that the greater dispersion of returns lead to higher gains and higher losses, which signifies the higher risk of an investment. From the low-ESG rating group, only the iShares MSCI Turkey (TUR ETF) experienced negative average returns of -2.70% and the highest volatility of 5.279 variance, First Trust NASDAQ Global Auto Index Fund (CARZ ETF) experienced the highest average return of 15.80%, and the second highest volatility of 5.11 variance. In terms of gains and losses, we can still consider these two ETFs to be consistent with Markowitz (1952) theory.

Table 1. Data statistics of High-ESG rating and Low-ESG rating ETFs.

High-ESG Rating ETFs	Mean	Variance	Skewness	Kurtosis
VanEck Semiconductor ETF (SMH)	0.175	6.278	-0.740	9.067
JPMorgan BetaBuilders Developed Asia ex-Japan ETF (BBAX)	0.050	3.23	3.227	13.749
iShares MSCI United Kingdom ETF (EWU)	0.0357	3.705	-1.328	14.767
iShares Global Financials ETF (IXG)	0.069	4.588	-1.087	14.601
iShares MSCI Pacific ex Japan ETF (EPP)	0.0515	3.877	-1.417	18.271
iShares MSCI Europe Financials ETF (EUFN)	0.047	5.696	-1.493	15.906
iShares MSCI-Australia ETF (EWA)	0.067	6.200	-1.348	18.161
Franklin FTSE United Kingdom ETF (FLGB)	0.044	3.471	-1.285	13.822
iShares MSCI Netherlands ETF (EWN)	0.138	3.070	-1.435	12.066
iShares MSCI Denmark ETF (EDEN)	0.139	2.333	-1.307	10.255
Nuveen ESG International Developed Markets Equity ETF (NUDM)	0.075	2.674	-1.797	17.348
First Trust Developed International Equity Select ETF (RNDM)	0.051	2.035	-2.183	21.497
Franklin FTSE Australia ETF (FLAU)	0.074	6.320	-1.653	20.491
Low-ESG Rating ETFs	Mean	Variance	Skewness	Kurtosis
Communication Services Select Sector SPDR Fund (XLC)	0.117	3.104	-1.026	12.971
Vanguard Communication Services ETF (VOX)	0.119	3.071	-1.128	13.512
Xtrackers Harvest CSI 300 China A-Shares ETF (ASHR)	0.067	3.207	-0.293	10.624
Fidelity MSCI Communication Services Index ETF (FCOM)	0.118	3.058	-1.101	12.831
KraneShares Bosera MSCI China A Share ETF (KBA)	0.083	3.103	-0.538	11.793
iShares MSCI China A ETF (CNYA)	0.084	2.993	-0.281	9.457
iShares MSCI Turkey ETF (TUR)	-0.027	5.279	-2.231	22.186
First Trust NASDAQ Global Auto Index Fund (CARZ)	0.158	5.111	-0.847	11.502
VanEck Vectors ChinaAMC SME-ChiNext ETF (CNXT)	0.112	4.289	-0.654	7.368
Xtrackers MSCI All China Equity ETF (CN)	0.044	2.929	-0.602	7.710
Global X MSCI China Consumer Staples ETF (CHIS)	0.072	3.765	-0.752	6.697
KraneShares CICC China Leaders 100 Index ETF (KFYP)	0.043	2.666	0.353	10.604
KraneShares Emerging Markets Healthcare Index ETF (KMED)	0.088	3.123	-0.832	6.404

Source: Yahoo! Finance; yahoofinance.com.

In general, the study found that low-ESG rating ETFs on average have slightly significant higher returns of 8.29% and also lower volatility of 3.52 compared to their high-ESG rating counterparts who have 7.82% returns and 4.11 variance. Surprisingly, this result is not consistent with the general positive perception of the market on business organizations with high-ESG ratings. The differing returns and volatility characteristics of the time-series data are also expected to yield differences in their forecast results. All of the high-ESG and low-ESG rating ETFs are negatively skewed, while the kurtosis coefficients of all ETFs have leptokurtic distributions. The above findings are not consistent with what Zhang et al. (2021) found that higher ESG rated companies have a lower implied volatility. However, the results are in-line with them exhibiting more negative implied skewness and higher implied kurtosis.

4.2. Lag innovations from ARMA-EGARCH models

Table 2.1 compares the findings of ARMA-EGARCH in determining the effects of lagged returns and volatilities. iShares MSCI Pacific ex Japan (EPP ETF) from high-ESG rating group showed strong auto-regressive process because of the significant constant, AR, and MA for the ARMA models. This implies that previous return values and error terms affect the current values of EPP ETFs, which help in determining their predictability. Other ETFs like iShares MSCI United Kingdom ETF (EWU ETF), Franklin FTSE United Kingdom ETF (FLGB ETF), NUDM ETF, and First Trust Developed International Equity Select ETF (RNDM ETF) both have significant values in AR and MA, thus, also shows possibility in their predictability properties. For the EGARCH models only RNDM ETF has both significant ARCH and GARCH models, which means that its current volatility has the possibility of being predicted by past volatilities. On the other hand, for the low-ESG rating group, Communication Services Select Sector SPDR Fund ETF (XLC), Vanguard Communication Services ETF (VOX), KraneShares CICC China Leaders 100 Index ETF (KFYP), and KraneShares Emerging Markets Healthcare Index ETF (KMED) have relatively strong auto-regressive process because of the significant values of AR and MA for the ARMA models. The above results on the effects of lagged returns are in-line with the past studies of Chen and Huang (2010) and Chen (2011), using ARMA-EGARCH estimations on both stock indices and ETF returns. For the EGARCH models only Xtrackers Harvest CSI 300 China A-Shares ETF (ASHR) and KraneShares Bosera MSCI China A Share ETF (KBA ETF) have significant numbers in the constant, ARCH and GARCH models, which means that its past volatilities can forecast current volatility, and help in the easier prediction of these time-series models. Other high-ESG and low-ESG rating ETFs have no convergence results, no significant numbers, or only one significant auto-regressive factor is present. These findings from the lagged volatility effects agree with Lin and Chiang (2005) in their research about the heightened volatility of component stocks after an ETF was created.

Table 2.1. Constant, lag ARMA, ARCH, and GARCH innovations from ARMA-EGARCH models.

High-ESG Rating ETFs	constant	AR	MA	constant	ARCH	GARCH
SMH	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.
BBAX	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.
EWU	0.029	-0.618***	0.471***	0.933*	-0.160	0.963***
	(0.524)	(0.000)	(0.000)	(0.078)	(0.578)	(0.000)
IXG	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.
EPP	0.096***	0.518**	-0.695***	0.855	2.829	0.899***
	(0.008)	(0.044)	(0.002)	(0.094)	(0.498)	(0.000)
EUFN	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.
EWA	0.067	-0.535**	0.347	1.319**	-0.318	0.963***
	(0.237)	(0.013)	(0.103)	0.030	(0.437)	(0.000)
FLGB	0.049	-0.625***	0.513***	0.887*	0.060	0.958***
	(0.306)	(0.000)	(0.000)	(0.064)	(0.874)	(0.000)
EWN	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.
EDEN	0.154***	-0.418	0.323	0.425*	0.086	0.930***

	(0.004)	(0.106)	(0.215)	(0.083)	(0.844)	(0.000)
NUDM	0.049	-0.535***	0.406***	0.642	-0.299	0.964***
	(0.283)	(0.000)	(0.002)	(0.244)	(0.279)	(0.000)
RNDM	0.053	-0.566***	0.419***	0.127	-0.613***	0.985***
	(0.178)	(0.000)	(0.001)	(0.819)	(0.003)	(0.000)
FLAU	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.
Low-ESG Rating ETFs	constant	AR	MA	constant	ARCH	GARCH
XLC	0.060	-0.678***	0.612**	0.853***	0.808	0.921***
	(0.271)	(0.003)	(0.012)	(0.004)	(0.598)	(0.000)
VOX	0.062	0.675**	0.606*	0.766**	1.037	0.916***
	(0.253)	(0.033)	(0.072)	(0.013)	(0.675)	(0.000)
ASHR	0.070	-0.343*	0.253	0.968***	2.125**	0.327*
	(0.349)	(0.076)	(0.208)	(0.000)	(0.041)	(0.064)
FCOM	0.070	-0.648**	0.576	0.743**	1.117	0.911***
	(0.197)	(0.048)	(0.106)	(0.011)	(0.673)	(0.000)
KBA	0.089	-0.329*	0.245	0.932***	1.603**	0.334**
	(0.226)	(0.067)	(0.171)	(0.000)	(0.046)	(0.019)
CNYA	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.
TUR	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.
CARZ	0.045	0.390	-0.315	1.492***	0.688	0.897***
	(0.682)	(0.374)	(0.452)	(0.000)	(0.360)	(0.000)
CNXT	0.111	-0.393	0.350	1.343***	2.876	0.333
	(0.248)	(0.115)	(0.150)	(0.000)	(0.294)	(0.398)
CN	0.069	0.354	0.322	0.939***	0.577	0.471
	(0.471)	(0.183)	(0.193)	(0.000)	(0.578)	(0.439)
CHIS	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.
KFYP	0.049	0.721***	0.697***	0.833***	0.780	0.605**
	(0.542)	(0.000)	(0.000)	(0.000)	(0.319)	(0.039)
KMED	0.055	-0.714***	0.599***	1.023***	2.271	0.808
	(0.428)	(0.000)	(0.001)	(0.000)	(0.536)	(0.000)

*Note: *, ** and *** are significance at 10, 5 and 1% levels, respectively; p-values are in parentheses; N.C. means no convergence.*

4.3. Lag innovations from ARMA-APARCH models

Table 2.2 compares the findings of ARMA-APARCH in determining the effects of lagged returns and volatilities. iShares MSCI Netherlands ETF (EWN) from high-ESG rating group showed strong auto-regressive process because of the significant constant, AR, and MA for the ARMA models. Other ETFs like IXG both have significant values in AR and MA, thus, also shows possibility in their predictability properties. For the EGARCH models only iShares Global Financials ETF (IXG) has significant constant, ARCH and GARCH models, which means that its current volatility has the possibility of being predicted by past volatilities. On the other hand, for the low-ESG rating group, Fidelity MSCI Communication Services Index ETF (FCOM), and Xtrackers MSCI All China Equity ETF (CN) have relatively strong auto-regressive process because of the significant values of AR and MA for the ARMA models. Chen and Huang (2010) and Chen (2011) had same results on the impacts of lagged returns using ARMA-EGARCH models on stock indices and ETF returns. For the EGARCH models only ASHR ETF have significant numbers in the constant, ARCH and GARCH models, which means that its previous volatilities can forecast current volatility, and help in the easier forecast of these time-series models. Other high-ESG and low-ESG rating ETFs have no convergence results, no significant numbers, or only one significant auto-regressive factor is present.

Table 2.2. Constant, lag ARMA, ARCH, and GARCH innovations from ARMA-APARCH models.

High-ESG Rating ETFs	constant	AR	MA	constant	ARCH	GARCH
SMH	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.

BBAX	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.
EWU	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.
IXG	0.073 (0.194)	-0.837*** (0.000)	0.874*** (0.000)	0.098** (0.040)	0.263*** (0.007)	0.737*** (0.000)
EPP	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.
EUFN	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.
EWA	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.
FLGB	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.
EWN	0.148*** (0.005)	-0.624*** (0.000)	0.487*** (0.000)	0.130** (0.016)	0.141 (0.419)	0.783*** (0.000)
EDEN	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.
NUDM	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.
RNDM	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.
FLAU	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.
Low-ESG Rating ETFs	constant	AR	MA	constant	ARCH	GARCH
XLC	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.
VOX	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.
ASHR	0.069 (0.331)	-0.362 (0.174)	0.285 (0.299)	0.612* (0.067)	0.289* (0.073)	0.512** (0.011)
FCOM	0.090 (0.203)	-0.734*** (0.000)	0.672*** (0.000)	0.136** (0.032)	0.153 (0.385)	0.772*** (0.000)
KBA	0.073 (0.279)	-0.434* (0.078)	0.378 (0.130)	0.687* (0.056)	0.301 (0.184)	0.478** (0.043)
CNYA	0.085 (0.221)	-0.402* (0.067)	0.331 (0.132)	0.945 (0.173)	0.332 (0.142)	0.374 (0.165)
TUR	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.
CARZ	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.
CNXT	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.
CN	0.049 (0.492)	-0.583*** (0.000)	0.535*** (0.000)	1.158 (0.257)	0.226 (0.171)	0.404 (0.172)
CHIS	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.
KFYP	0.046 (0.517)	-0.556 (0.494)	0.548 (0.458)	1.788 (0.688)	0.086 (0.748)	0.358 (0.300)
KMED	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.

*Note: *, ** and *** are significance at 10, 5 and 1% levels, respectively; p-values are in parentheses; N.C. means no convergence.*

4.4. Lag innovations from ARFIMA-FIEGARCH models

Tables 2.3 compares the findings of ARFIMA-FIEGARCH in determining the effects of lagged returns and volatilities. For high-ESG rating group, JPMorgan BetaBuilders Developed Asia ex-Japan ETF (BBAX) and FLAU ETFs showed strong auto-regressive process because of the significant constant, AR, and MA for the ARFIMA models. Other ETFs like EPP, EWN, EDEN, and NUDM have significant values in AR and MA, thus, also shows possibility in their predictability properties. For the FIEGARCH models, BBAX, NUDM, and FLAU ETFS have significant constant, ARCH and GARCH models, which means that its current volatility has the possibility of being predicted by past volatilities. On the other hand, for the low-ESG rating group, ASHR, and iShares MSCI China A ETF (CNYA) have relatively strong auto-regressive process because of the significant values of the constant, AR and MA for the ARFIMA models. Other ETFs like XLC, VOX, and CARZ ETFs have significant values in AR and MA, thus, also shows possibility in their predictability properties. These outcomes on the effects of lagged returns are again in-line with the previous studies of Chen and Huang (2010) and Chen (2011). For the FIEGARCH models only TUR and KMED ETFs have significant numbers in the constant, ARCH and GARCH models, which means that its past volatilities can forecast current volatility, and help in the easier prediction of these time-series models. Other high-ESG and low-

ESG rating ETFs have no convergence results, no significant numbers, or only one significant auto-regressive factor is existing.

Table 2.3. Constant, lag ARMA, ARCH, and GARCH innovations from ARFIMA-FIEGARCH models.

High-ESG Rating ETFs	constant	AR	MA	constant	ARCH	GARCH
SMH	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.
BBAX	0.060*	-0.544***	0.457***	3.152***	-0.865***	0.576***
	(0.082)	(0.000)	(0.006)	(0.001)	(0.000)	(0.000)
EWU	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.
IXG	0.071	0.406	-0.232	1.697***	0.857**	-0.237
	(0.214)	(0.453)	(0.593)	(0.003)	(0.048)	(0.255)
EPP	0.054	-0.560***	0.475***	2.896	0.511	0.231
	(0.143)	(0.002)	(0.008)	(0.117)	(0.907)	(0.819)
EUFN	0.061	0.255	-0.116	2.348**	1.548	-0.348
	(0.308)	(0.316)	(0.576)	(0.012)	(0.304)	(0.328)
EWA	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.
FLGB	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.
EWN	0.021	-0.586***	0.439***	1.636***	0.707	0.006
	(0.831)	(0.000)	(0.000)	(0.001)	(0.219)	(0.982)
EDEN	0.096	-0.566***	0.506***	1.299***	0.709	-0.180
	(0.156)	(0.000)	(0.001)	(0.007)	(0.271)	(0.391)
NUDM	0.066	-0.555***	0.499***	1.899***	-0.991***	0.357**
	(0.124)	(0.000)	(0.000)	(0.010)	(0.000)	(0.044)
RNDM	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.
FLAU	0.083**	-0.499***	0.421***	3.802***	-0.786***	0.504***
	(0.019)	(0.000)	(0.005)	(0.000)	(0.000)	(0.000)
Low-ESG Rating ETFs	constant	AR	MA	constant	ARCH	GARCH
XLC	0.058	-0.699***	0.681***	1.737***	1.237	0.470
	(0.474)	(0.000)	(0.000)	(0.005)	(0.544)	(0.235)
VOX	0.068	-0.689***	0.658***	1.675*	2.036	0.494**
	(0.472)	(0.007)	(0.008)	(0.052)	(0.702)	(0.024)
ASHR	0.077**	0.494***	-0.410***	1.128***	2.207**	0.097
	(0.050)	(0.001)	(0.003)	(0.001)	(0.022)	(0.618)
FCOM	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.
KBA	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.
CNYA	0.106**	0.569***	0.478***	1.100***	1.082	0.051
	0.017	(0.000)	(0.000)	(0.008)	(0.113)	(0.797)
TUR	-0.042*	0.810***	-0.254*	2.948***	2080.880**	-0.762***
	(0.098)	(0.000)	(0.090)	(0.000)	(0.023)	(0.000)
CARZ	-0.162	-0.602***	0.533***	2.350***	0.817	0.002
	(0.438)	(0.000)	(0.001)	(0.000)	(0.378)	(0.994)
CNXT	0.106	0.680*	-0.447	1.449**	2.433	0.577
	(0.275)	(0.096)	(0.255)	(0.024)	(0.714)	(0.440)
CN	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.
CHIS	0.152*	-0.618	0.567	1.415***	0.484	0.701**
	(0.068)	(0.422)	(0.492)	(0.008)	(0.715)	(0.019)
KFYP	0.054**	0.358**	-0.161	1.003***	1.534*	-0.109
	(0.015)	(0.035)	(0.244)	(0.006)	(0.085)	(0.585)
KMED	-0.067	-0.345	0.186	2.335***	-0.759***	0.585***
	(0.678)	(0.234)	(0.566)	(0.000)	(0.006)	(0.000)

*Note: *, ** and *** are significance at 10, 5 and 1% levels, respectively; p-values are in parentheses; N.C. means no convergence.*

4.5. Lag innovations from ARFIMA-FIAPARCH models

Table 2.4 compares the findings of ARFIMA-FIAPARCH in determining the effects of lagged returns and volatilities. For high-ESG rating group, BBAX, EWU, iShares MSCI Denmark ETF (EDEN), NUDM, and RNDM ETFs showed strong auto-regressive process because of the significant constant, AR, and MA for the ARFIMA models. For the FIEGARCH models, BBAX, NUDM, and FLAU ETFS have significant ARCH and GARCH models, which is consistent from the ARMA-EGARCH findings. On the other hand, for the low-ESG rating group, XLC, VOX, FCOM, KBA, CNYA, and VanEck Vectors ChinaAMC SME-ChiNext ETF (CNXT) have relatively strong auto-regressive process because of the significant values of the constant, AR and MA for the ARFIMA models. Other ETFs like CARZ and CN ETFs have significant values in AR and MA, thus, also shows possibility in their predictability properties. For the FIEGARCH models no ETFs have significant numbers in at least both the ARCH and GARCH models. Other high-ESG and low-ESG rating ETFs have no convergence results, no significant numbers, or only one significant auto-regressive factor is present. The outcomes are also in-line with the previous findings of Fama (1965), Engle (1982) and Koutmos et al. (1994) in their study of leverage effects and volatility clustering. Aside from these earlier foundationa research, the findings of this paper are again also connected with the recent studies of Chen and Huang (2010), Chen and Diaz (2013a and 2013b) when they found volatility clustering in the returns and volatilities of equity, faith and leveraged ETFs, respectively.

Table 2.4. Constant, lag ARMA, ARCH, and GARCH innovations from ARFIMA-FIAPARCH models.

High-ESG Rating ETFs	constant	AR	MA	constant	ARCH	GARCH
SMH	0.167***	-0.577	0.498	0.114	0.040	0.203
	(0.006)	(0.274)	(0.457)	(0.830)	(0.859)	(0.488)
BBAX	0.0504*	-0.964***	0.979***	-0.071	-0.781 ***	-0.729***
	(0.095)	(0.000)	(0.000)	(0.806)	(0.000)	(0.000)
EWU	0.055*	-0.729***	0.682**	0.168	-0.691**	-0.563
	(0.063)	(0.002)	(0.036)	(0.619)	(0.046)	(0.225)
IXG	0.104**	0.265	-0.111	0.183	-0.355	-0.149
	(0.014)	(0.698)	(0.822)	(0.449)	(0.276)	(0.685)
EPP	0.054	-0.063	0.042	0.107	-0.391	-0.060
	(0.175)	(0.929)	(0.937)	(0.522)	(0.135)	(0.892)
EUFN	0.076	0.168	-0.027	-0.300	-0.633	-0.451
	(0.107)	(0.393)	(0.854)	(0.829)	(0.343)	(0.728)
EWA	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.
FLGB	0.064**	-0.674	0.650	0.248	-0.635***	-0.356
	(0.047)	(0.166)	(0.215)	(0.310)	(0.001)	(0.246)
EWN	0.112	-0.622***	0.491***	0.089	-0.154	0.026
	(0.124)	(0.000)	(0.000)	(0.667)	(0.401)	(0.880)
EDEN	0.144***	-0.554***	0.501***	0.190	-0.291	0.151
	(0.000)	(0.001)	(0.001)	(0.484)	(0.139)	(0.365)
NUDM	0.067**	0.915***	0.947***	-0.227	-0.847***	-0.834***
	(0.017)	(0.000)	(0.000)	(0.593)	(0.000)	(0.001)
RNDM	0.067***	-0.666***	0.613***	-0.241**	0.355***	0.134
	(0.003)	(0.000)	(0.000)	(0.046)	(0.000)	(0.116)
FLAU	0.066	-0.643***	0.532***	-0.447	-0.970***	0.977***
	(0.173)	(0.000)	(0.002)	(0.376)	(0.000)	(0.000)
Low-ESG Rating ETFs	**constant**	**AR**	**MA**	**constant**	**ARCH**	**GARCH**
XLC	0.103***	-0.679***	0.658***	-0.505	-0.533	-0.466
	(0.002)	(0.001)	(0.000)	(0.359)	(0.162)	(0.287)
VOX	0.099**	0.714 ***	0.685***	-0.351	-0.599	-0.549
	(0.023)	(0.000)	(0.000)	(0.579)	(0.201)	(0.308)
ASHR	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.

FCOM	0.097** (0.031)	-0.714*** (0.000)	0.688*** (0.000)	-0.330 (0.622)	-0.605 (0.332)	-0.558 (0.427)
KBA	0.107*** (0.001)	0.545*** (0.000)	0.386*** (0.001)	0.585*** (0.005)	-0.442** (0.026)	-0.230 (0.412)
CNYA	0.097*** (0.005)	0.547*** (0.001)	-0.424*** (0.007)	0.541 (0.197)	0.597*** (0.000)	0.286 (0.121)
TUR	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.
CARZ	0.019 (0.909)	-0.539*** (0.006)	0.471** (0.023)	-0.120 (0.785)	-0.302* (0.051)	-0.107 (0.583)
CNXT	0.131*** (0.003)	0.643*** (0.000)	-0.429*** (0.006)	0.798 (0.196)	-0.271 (0.108)	-0.109 (0.711)
CN	0.045 (0.510)	-0.620*** (0.000)	0.581*** (0.000)	0.439 (0.531)	0.474*** (0.001)	0.232 (0.218)
CHIS	0.121 (0.141)	-0.534 (0.302)	0.497 (0.370)	0.345 (0.381)	-0.334 (0.408)	-0.137 (0.801)
KFYP	0.051* (0.053)	0.338 (0.154)	-0.161 (0.367)	0.646 (0.117)	-0.531 (0.388)	-0.389 (0.658)
KMED	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.

*Note: *, ** and *** are significance at 10, 5 and 1% levels, respectively; p-values are in parentheses; N.C. means no convergence.*

4.6. Analyses using ARMA-APARCH and ARFIMA-FIAPARCH models

Table 3.1 compares the results of short-memory and long-memory models, and presents analyses on the asymmetric volatility properties of High ESG rating and Low ESG rating returns and volatility performance. In determining the effects of lagged volatilities (APARCH coefficient), ARMA-APARCH show a more consistent influence of previous volatility innovations for IXG and EWN ETFs for high-ESG rating ETFs; and ASHR, CNYA and CN ETFs for low-ESG rating ETFs. However, for most high-ESG rating and low-ESG ratings ETFs no convergence in the statistical calculation was met, and some didn't meet the significance level. The significant positive gamma parameter for IXG ETF from the ARMA-APARCH models show that the high-ESG rating ETF exhibit asymmetric volatility properties, which means that this ETF possess asymmetric volatility property. Again, for most high-ESG rating and low-ESG ratings ETFs no convergence was observed, and some didn't meet the significance level.

The asymmetric volatility property of IXG ETF answers the third objective of this research and suggests that the ETF with the significant result is not resistant to negative shocks, which means that bad news have greater negative impact on their return and volatility performance than good news. Chen (2011), and Chen and Diaz (2012) earlier observed this phenomenon with regards to their studies on ethical and faith-based ETFs, respectively; and concluded that this characteristic is common to investment instruments. Another earlier research of Bekaert and Wu (2000) explained that because of the high volatility feedback mechanism, negative shocks increase conditional variances in the financial markets substantially. Tan and Khan (2010) particularly observed these in their study of Malaysian stock markets during the 2008 Great Recession. These results suggest that portfolio managers should not treat high-ESG rating or ethical financial companies as safe haven portfolios in times of economic downturns. Although returns of ethical financial companies are higher and their volatility are steadier, but like many other investments they are also vulnerable to bad economic fundamentals.

One of the important characteristics of the ARFIMA-FIAPARCH models is its long-memory parameter through the d-coefficient, which determines the probability of forecasting a given time-series data. Findings on the returns d-coefficient showed that NUDM ETF of the high-ESG rating ETFs and XLC, KBA CNYA, and KMED ETFs from low-ESG rating ETFs denote a stationary data, but a non-invertible process. This data characteristic means that the data time-series cannot be represented by any AR model. Furthermore, long-memory properties were evident in the volatility d-coefficient wherein most of the findings showed significant results for high-ESG ETFs except for SMH, iShares MSCI Europe Financials ETF (EUFN), EWN, and RNDM ETFs. Low-ESG rating ETFs have lower existence of significant numbers like XLC, VOX, FCOM, KBA, and CARZ ETFs. These results do not really conform to the objective of this research regarding the dual long-memory process in the stock returns and volatilities. Nevertheless, findings still suggest that volatility structures of high-ESG rating and low-ESG rating ETFs under study have signs of market inefficiency and investors may possibly earn excess returns or can minimize losses by properly modeling their volatility movements from previous prices.

These findings offer a glaring divergence from the weak-form EMH of Fama (1970) explaining that excess returns cannot be gained in the long run through data mining, because future time-series cannot be forecasted by analyzing previous prices. However, parallel with the results of this paper, empirical evidences regarding the predictability of some investment instruments using technical analysis have been documented by the studies on the South Korean, Turkish, Malaysian and Philippine stock markets of Kang and Yoon (2007), Korkmaz et al. (2009), Tan and Khan (2010), Chen and Diaz (2014), respectively. These also explain why data mining and technical analysis utilizing advanced mathematical tools are growing exponentially in years.

The significant positive gamma parameter for EWU, Franklin FTSE United Kingdom ETF (FLGB), EDEN, and RNDM ETFs for high-ESG rating ETFs; and XLC, VOX, FCOM, and CARZ ETFs from the ARFIMA-FIAPARCH models show that both high-ESG and low-ESG rating ETFs exhibit asymmetric volatility properties, which means that these ETFs possess asymmetric volatility property. Again, for some high-ESG rating and low-ESG ratings ETFs no convergence was observed, and some didn't meet the significance level. The asymmetric volatility property of these ETFs answers the objective of this research and suggests that the ETF with the significant result is not immune to negative shocks, which means that bad news have stronger negative effect on their return and volatility performance than good news. Cochrana et al. (2012) have findings consistent with the above results when they studied the futures markets.

Table 3.1. Long-memory and asymmetric volatility analyses using ARMA-APARCH and ARFIMA-FIAPARCH models.

ARMA-APARCH models				ARFIMA-FIAPARCH models				
High-ESG Rating ETFs	APARCH	gamma	log-likelihood	returns d-coeff.	FIAPARCH	volatility d-coeff.	gamma	log-likelihood
SMH	N.C.	N.C.	-832.305	-0.081 (0.507)	1.816*** (0.000)	0.343 (0.141)	0.269 (0.231)	-831.730
BBAX	N.C.	N.C.	-630.322	-0.092 (0.119)	1.837*** (0.000)	0.317*** (0.007)	0.242 (0.235)	-639.292
EWU	N.C.	N.C.	-682.803	-0.105 (0.152)	1.735*** (0.000)	0.421*** (0.001)	0.2778** (0.036)	-680.236
IXG	1.304** (0.039)	0.347** (0.045)	-703.814	-0.109 (0.559)	1.491*** (0.000)	0.439*** (0.002)	0.384 (0.127)	-701.300
EPP	N.C.	N.C.	-628.522	-0.093 (0.552)	1.723*** (0.001)	0.483* (0.095)	0.185 (0.598)	-644.238
EUFN	N.C.	N.C.	-780.701	-0.148 (0.257)	1.903*** (0.000)	0.366 (0.290)	0.356 (0.348)	-778.860
EWA	N.C.	N.C.	-699.250	N.C.	N.C.	N.C.	N.C.	-697.131
FLGB	N.C.	N.C.	-676.850	-0.088 (0.203)	1.597*** (0.000)	0.460*** (0.004)	0.301** (0.036)	-674.663
EWN	1.610** (0.015)	0.569 (0.274)	-675.319	0.011 (0.879)	1.456 (0.000)	0.297 (0.005)	0.783 (0.004)	-669.841
EDEN	N.C.	N.C.	-642.477	-0.063 (0.235)	1.522*** (0.001)	0.311*** (0.010)	0.479** (0.021)	-642.900
NUDM	N.C.	N.C.	-605.310	-0.119** (0.040)	1.819*** (0.000)	0.248*** (0.008)	0.395 (0.168)	-607.316
RNDM	N.C.	N.C.	-541.105	-0.104	3.254***	0.005	0.394***	-538.962

				(0.248)	(0.000)	(0.113)	(0.002)	
FLAU	N.C.	N.C.	-686.335	-0.034 (0.671)	1.668*** (0.000)	0.206*** (0.000)	0.612 (0.135)	-697.452
Low-ESG Rating ETFs	APARCH	gamma	log-likelihood	returns d-coeff.	FIAPARCH	volatility d-coeff.	gamma	log-likelihood
XLC	N.C.	N.C.	-671.107	-0.099* (0.100)	1.944*** (0.000)	0.156** (0.041)	0.633** (0.040)	-665.858
VOX	N.C.	N.C.	-666.052	-0.062 (0.257)	1.857*** (0.000)	0.145* (0.089)	0.705* (0.055)	-661.994
ASHR	1.856*** (0.010)	0.077 (0.720)	-747.877	N.C.	N.C.	N.C.	N.C.	-743.489
FCOM	1.842 (0.269)	0.317 (0.318)	-668.500	-0.062 (0.263)	1.854*** (0.000)	0.152* (0.059)	0.674* (0.073)	-662.417
KBA	2.264*** (0.004)	0.100 (0.647)	-735.047	-0.204** (0.016)	1.634*** (0.007)	0.485* (0.080)	-0.002 (0.993)	-731.688
CNYA	2.543* (0.061)	0.154 (0.382)	-734.632	-0.177* (0.088)	3.090** (0.011)	0.027 (0.587)	0.076 (0.681)	-732.234
TUR	N.C.	N.C.	-882.774	N.C.	N.C.	N.C.	N.C.	-895.112
CARZ	N.C.	N.C.	-795.147	0.096 (0.145)	1.692*** (0.000)	0.270* (0.057)	0.759*** (0.005)	-795.971
CNXT	N.C.	N.C.	-817.991	-0.226 (0.186)	1.892*** (0.000)	0.234 (0.230)	0.094 (0.715)	-823.747
CN	3.467 (0.064)	0.127 (0.508)	-733.203	-0.014 (0.820)	3.839*** (0.005)	0.008 (0.631)	0.176 (0.371)	-731.286
CHIS	N.C.	N.C.	-780.751	-0.016 (0.783)	2.111*** (0.000)	0.331 (0.115)	-0.039 (0.758)	-787.663
KFYP	6.088 (0.430)	-0.067 (0.587)	-711.319	-0.222** (0.039)	1.544*** (0.000)	0.427 (0.172)	-0.086 (0.623)	-709.264
KMED	N.C.	N.C.	-730.776	N.C.	N.C.	N.C.	N.C.	-726.469

*Note: *, ** and *** are significance at 10, 5 and 1% levels, respectively; p-values are in parentheses; N.C. means no convergence.*

4.7. Analyses using ARMA-EGARCH and ARFIMA-FIEGARCH models

Table 3.2 compare the results of short-memory and long-memory models, and presents analyses on the asymmetric volatility properties of High ESG rating and Low ESG rating returns

and volatility performance. In determining the effects of lagged volatilities (EGARCH coefficient), ARMA-EGARCH models show a more consistent influence of previous volatility innovations for FLGB, EDEN, NUDM, and RNDM ETFs for high-ESG rating ETFs; and only CARZ ETF for the low-ESG rating. However, for most high-ESG rating and low-ESG ratings ETFs no convergence in the statistical calculation was met, and some didn't meet the significance level

The significant positive theta parameter for EWU, EWA, FLGB, EDEN, and NUDM ETFs from high-ESG rating ETFs; and ASHR, KBA, CARZ, and KraneShares CICC China Leaders 100 Index ETF (KFYP) from low-ESG rating ETFs from the ARMA-EGARCH models show that the exhibit leverage effects properties, which means that volatility clustering happens, and negative shocks produce more fluctuations in time-series data of both high-ESG rating and low-ESG rating ETFs. For some high-ESG rating and low-ESG ratings ETFs no convergence was observed, and some didn't meet the significance level. The leverage effects property of IXG ETF answers the second objective of this research and suggests that the ETF with the significant result is not immune to bad economic news and have stronger negative effect on their return and volatility performance. This characteristic is again common to all financial instruments, and are in-line with the results of Chen (2011), and Chen and Diaz (2012).

One of the significant features of the ARFIMA-FIEGARCH models is its long-memory parameter through the d-coefficient, which determines the predictability of a given time-series data. Findings on the returns d-coefficient showed that no ETFs from the high-ESG rating ETFs exhibit long-memory properties using these models. However, ASHR, TUR, CNXT, and KFYP ETFs from low-ESG rating ETFs generally denote a stationarity, but non-invertible process, which means that the data time-series cannot be represented by any AR model. Positive dependence properties were evident in the volatility d-coefficient wherein most of the findings showed significant results for high-ESG ETFs except for EWU, EWA, FLGB, and RNDM ETFs. Low-ESG rating ETFs also observed significant numbers except for FCOM, KBA, CNYA, CNXT, CN, and Global X MSCI China Consumer Staples ETF (CHIS). These findings do not really correspond to the objective of this research regarding the dual long-memory process in the ESG rating ETF returns and volatilities. Nevertheless, results still indicate that volatility structures of high-ESG rating and low-ESG rating ETFs under study have signs of market inefficiency and investors can minimize losses or benefit from excess returns or by properly modeling their volatility fluctuations from previous prices. These findings again offer a stark contrast on the weak-form EMH of Fama (1970) which explained that excess returns cannot be gained in the long run through data mining.

The significant positive theta parameter for BBAX, IXG, EWN, EDEN, and NUDM ETFs for high-ESG rating ETFs; and ASHR, CNYA, TUR, CARZ, KFYP, and KMED ETFs for low-ESG rating ETFs from the ARFIMA-FIEGARCH models show that both ESG rating ETFs group exhibit leverage effects, which means that volatility clustering exists during times of negative economic news. Again, for some high-ESG rating and low-ESG ratings ETFs no convergence was observed, and some didn't meet the significance level. The leverage effects property of these ETFs answer the second objective of this research and suggests that the ETF with the significant result is not immune to negative shocks, which means that bad news have stronger negative effect on their return and volatility performance than good news.

In identifying the best fitting models for the High ESG rating and Low ESG rating ETFs, this study utilized the maximum log-likelihood values. Generally, the long-memory models, ARFIMA-FIAPARCH and ARFIMA-FIEGARCH models consistently are the better fitting models outperform their short-memory counterparts, ARMA-APARCH and ARMA-EGARCH models. The FI models are also better at capturing volatility asymmetry with the presence of more significant numbers for both ETF groups. This result is in-line with the objective of this paper, and is connected with the studies on the Istanbul stock exchange, commodity futures, and the Bombay stock exchange by Ruzgar and Kale (2007), Tansuchat et al. (2009), and Goudarzi (2010), respectively; these studies demonstrated the power of long-memory models using time-series data. The power of FI models is said to be statistically credited to the hyperbolic rate of decay present compared to the exponential rate of decay in short memory models; and the allowance given to the difference parameter to be a non-integer offering greater flexibility in modeling time-series data. These results suggest that technical analysts should focus on the use of long-memory models in modeling financial time-series.

Table 3.2. Long-memory and asymmetric volatility analyses using ARMA-EGARCH and ARFIMA-FIEGARCH models.

	ARMA-EGARCH models			ARFIMA-FIEGARCH models				
High-ESG Rating ETFs	Theta 1 EGARCH	Theta 2	log-likelihood	returns d-coeff.	Theta 1 FIEGARCH	volatility d-coeff.	Theta 2	log-likelihood
SMH	N.C.	N.C.	-841.713	N.C.	N.C.	N.C.	N.C.	-833.054
BBAX	N.C.	N.C.	-651.663	-0.056 (0.402)	-0.059 (0.469)	1.093*** (0.006)	0.358*** (0.000)	-638.552
EWU	-0.104 (0.130)	0.473*** (0.007)	-691.874	N.C.	N.C.	N.C.	N.C.	-679.377
IXG	N.C.	N.C.	-703.799	-0.130 (0.399)	-0.223*** (0.005)	0.584*** (0.000)	0.413*** (0.000)	-699.429
EPP	0.024 (0.141)	0.179 (0.285)	-651.475	-0.089 (0.212)	-0.029 (0.712)	0.721*** (0.005)	0.284 (0.240)	-639.466

EUFN	N.C.	N.C.	-790.871	-0.154 (0.137)	-0.124 (0.246)	0.658*** (0.000)	0.199 (0.125)	-778.211
EWA	-0.137 (0.229)	0.538*** (0.000)	-724.887	N.C.	N.C.	N.C.	N.C.	-714.472
FLGB	-0.089* (0.099)	0.380*** (0.001)	-687.492	N.C.	N.C.	N.C.	N.C.	-673.472
EWN	N.C.	N.C.	-678.647	0.030 (0.693)	-0.219*** (0.001)	0.596*** (0.000)	0.213* (0.038)	-669.444
EDEN	-0.117** (0.028)	0.284** (0.019)	-648.871	-0.054 (0.358)	-0.183** (0.017)	0.603*** (0.000)	0.269* (0.096)	-643.048
NUDM	-0.134* (0.100)	0.438*** (0.001)	-621.392	-0.073 (0.271)	-0.166** (0.043)	1.475*** (0.000)	0.345*** (0.001)	-607.707
RNDM	-0.278*** (0.010)	0.215 (0.235)	-556.576	N.C.	N.C.	N.C.	N.C.	-538.956
FLAU	N.C.	N.C.	-717.752	-0.095 (0.224)	-0.064 (0.402)	1.002*** (0.000)	0.363*** (0.001)	-696.547
Low-ESG Rating ETFs	APARCH	gamma	log-likelihood	returns d-coeff.	APARCH	volatility d-coeff.	gamma	log-likelihood
XLC	-0.058 (0.452)	0.233 (0.151)	-675.625	-0.080 (0.257)	-0.063 (0.441)	0.571*** (0.000)	0.114 (0.287)	-667.203
VOX	-0.056 (0.571)	0.216 (0.310)	-668.870	-0.068 (0.408)	-0.043 (0.707)	0.557*** (0.000)	0.100 (0.486)	-661.738
ASHR	-0.047 (0.353)	0.277** (0.018)	-743.870	-0.148* (0.074)	-0.039 (0.421)	0.269** (0.039)	0.287** (0.012)	-740.252
FCOM	-0.047 (0.611)	0.218 (0.307)	-669.024	N.C.	N.C.	N.C.	N.C.	-662.408
KBA	-0.065 (0.298)	0.328** (0.024)	-733.631	N.C.	N.C.	N.C.	N.C.	-730.087
CNYA	N.C.	N.C.	-735.753	-0.157 (0.131)	-0.072 (0.382)	0.280 (0.131)	0.404** (0.042)	-733.259
TUR	N.C.	N.C.	-894.729	-0.529*** (0.001)	0.000** (0.012)	0.696*** (0.000)	0.000*** (0.000)	-861.154
CARZ	-0.120* (0.074)	0.270*** (0.004)	-810.606	0.098 (0.126)	-0.189** (0.021)	0.580*** (0.000)	0.193*** (0.002)	-796.717
CNXT	-0.065 (0.376)	0.103 (0.169)	-823.959	-0.251* (0.088)	-0.024 (0.840)	0.186 (0.773)	0.100 (0.520)	-823.380
CN	-0.087 (0.305)	0.411 (0.032)	-738.035	N.C.	N.C.	N.C.	N.C.	-733.949
CHIS	N.C.	N.C.	-790.248	0.000 (0.997)	0.004 (0.960)	0.287 (0.325)	0.231 (0.108)	-789.426
KFYP	0.006 (0.924)	0.385*** (0.000)	-713.208	-0.256*** (0.001)	0.017 (0.754)	0.317* (0.081)	0.354*** (0.003)	-706.973
KMED	-0.005 (0.838)	0.133 (0.322)	-745.756	0.083 (0.252)	-0.177* (0.065)	0.849*** (0.001)	0.230*** (0.009)	-731.055

*Note: *, ** and *** are significance at 10, 5 and 1% levels, respectively; p-values are in parentheses; N.C. means no convergence.*

5. Conclusions and Limitations

The research compared short-memory models, ARMA-EGARCH and ARMA-APARCH; and long-memory models, ARFIMA-FIEGARCH and ARFIMA-FIAPARCH, to examine return and volatility performance of high-ESG and low-ESG rating ETFs.

Regarding the returns and volatility comparison, Low-ESG rating ETFs showed slightly higher average returns and lower volatility compared to their High-ESG counterparts. These results diverge from the general market perception favoring companies with high ESG ratings. Findings from ARMA-EGARCH, ARMA-APARCH, ARFIMA-FIEGARCH, and ARFIMA-FIAPARCH models revealed varying degrees of predictability across different ETFs. Generally, long-memory models exhibited better fitting and predictive capabilities, particularly in capturing volatility asymmetry, which aligns with previous studies emphasizing the efficacy of long-memory models in financial time-series analysis.

Furthermore, results indicated the presence of asymmetric volatility properties in both High-ESG and Low-ESG rating ETFs, implying that negative shocks have a stronger impact on returns and volatility performance compared to positive ones. These findings underscore the importance of considering asymmetry in risk management and portfolio construction strategies. While some ETFs exhibited characteristics of long-term dependence, particularly in volatility, the overall findings did not strongly support the presence of dual long-memory processes. However, they suggest potential market inefficiencies that investors can exploit through proper modeling of volatility movements.

The research recommends that investors and fund managers who constantly rebalance their portfolios to carefully assess the returns of both and low-ESG rating ETFs, because holdings in low-ESG ratings can also give relatively higher returns than high-ESG rating ETFs. Although fundamentally, the investing world is getting more conscious of the direction towards ESG-related investment and this would give higher earnings potential in the future. However, this paper found that ESG-rated ETFs are also vulnerable to negative shocks, which suggests that investors should not consider high-ESG rating ETFs as safe haven portfolios especially in times of economic uncertainties. Nonetheless, analysts in the future should see the potential of long-memory methodologies in modeling financial time-series of these groups of ETFs, given that technical analysis can still be a potent tool in trying to predict their future price movements.

Given the above contributions, the study is not without its limitations. For example, the paper did not specify the type of forecast that can fit the time-series data after determining the predictable structures of the time-series. In forthcoming research, it is important to delineate one-step ahead and two-step ahead forecasts, along with their extensions, for time-series data analysis. Expanding the data to include events such as the COVID-19 pandemic and the 2008 subprime mortgage crisis to employ structural break tests, including the ICSS algorithm or the Chow Structural Breakpoint test is also a valuable extension of the study. Future investigations can extend the dataset to understand changes in return and volatility characteristics of ETFs prior to, during, and post-crisis periods. Moreover, this study delved into ETFs categorized by high and low ESG ratings, subjected solely to designated FI tests. Future papers can also apply more advanced methodologies in the FI family of models like the Orthogonal GARCH (OGARCH) or the Hyperbolic GARCH (HYGARCH), and utilize them to determine other types of ETFs in other sectors or industries. Despite these limitations, this paper can still serve as a stepping stone for both the academic community and the investing public in the proper modeling of high-ESG and low-ESG rating ETFs. The conclusions can offer researchers and academicians additional future research channels about the financial time-series properties of high-ESG and low-ESG rating ETFs. Also, the existence of asymmetric volatility and long-memory properties can guide the investing in building investment portfolios that can possibly minimize losses and maximize gains from careful application of return and volatility models.

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Conflict of interest

All the authors claim that the manuscript is completely original. The authors also declare no conflict of interest.

Author contributions

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