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FRACTIONAL INTEGRATION IN CORPORATE SOCIAL RESPONSIBILITY INDICES: A FIGARCH AND HYGARCH APPROACH

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ABSTRACT

This research focuses on studying the return and volatility of CSR indices. Four models namely ARFIMA, ARFIMA-GARCH, ARFIMA-FIGARCH and ARFIMA-HYGARCH were applied to investigate the long-memory process in these indices. This paper provides investors with knowledge of CSR indices' time-series data structure, and identifies the most suitable model for volatility estimation. The dataset included 16 CSR indices in terms of environmental, social and corporate governance performance (ESG) under four categories regarding different regional markets in the world. The results show that all the indices exhibit long-memory process, which indicates that predicting their CSR index volatilities in the future to gain excess profits is feasible. In addition, based on log-likelihood values, ARFIMA-HYGARCH appears as the best fitting model to estimate the long-memory effect over the other GARCH models. This paper acknowledges the increasing importance of CSR in selecting investment portfolios to not just maximize returns, but to also promote responsible financing.

Contribution/ Originality: This study bridges the gap to the existing literature by utilizing the estimating and predicting functions of GARCH-family models, especially HYGARCH model, to examine the long-memory property of CSR indices. The findings provide practical knowledge and tools for green investors to enhance their portfolio performance.

1. INTRODUCTION

Corporate social responsibility (CSR) has become a business model in recent decades that aims for the self-regulation of corporations, and integration of CSR into the core of business operations. CSR serves as a mechanism where a business monitors and ensures its active compliance with the law, demonstration of ethical standards, and observance of both local and international norms. There have been numerous definitions proposed in the literature of CSR (Holme and Watts, 2000; Frederick 2008; Aguinis, 2011) and most of them agree on and cover the core meaning of CSR initiatives which indicates a firm's responsibility to, through its policies and decisions, improve the well-being of the society and environment that may be affected by its economic operations.

With the recent wave of catastrophic economic meltdown, financial markets are practically encouraged to adopt and publicly report their CSR performances. Adopting CSR is considered as a strategic move for companies, because of peer-pressure in the business environment, as well as consumer's expectations. Besides improving reputation, strengthening public relations, and dispersing risks, CSR also fosters financial performances as it satisfies various stakeholders, which attracts more investments. Table 1 shows the report released by the Global Sustainable Investment Alliance in 2017. According to their findings, global SRI asset values grew by 25%, from USD18.28 trillion to USD 22.89 trillion, in the two-year period from 2014 to 2016.

Table-1. Growth of SRI Assets by Region 2014-2016.

Region	2014	2016	Growth over period
Europe	10,775	12,040	11.7%
United States	6,572	8,723	32.7%
Canada	729	1,086	49.0%
Australia/New Zealand	148	516	247.5%
Asia (excluding Japan)	45	52	15.7
Japan	7	474	6,689.6%
Total	*18,276*	*22,890*	*25.2%*

Note: Asset values are expressed in USD billions.
Source: Global Sustainable Investment Review of 2016.

Along with the growth of CSR initiatives, the numbers of investors interested in "green investment" or "ethical investment" or "socially responsible investment" (SRI) is also gaining traction. In fact, these terms are normally used interchangeably, which refers to "the exercise of ethical and social criteria in the selection and management of investment portfolios, generally consisting of company shares" (Cowton, 1994). SRI has grown significantly and reached a maturity level in recent years when it actually has become part of mainstream investments practice (Sparkes and Cowton, 2004). Accordingly, as shown in Table 2, most of the regions in the world showed increases in SRI assets managed relative to the total portfolio of investments. The biggest jump came from the combined assets of Australia and New Zealand.

Table-2. Proportion of SRI Relative to Total Managed Assets.

Region	2014	2016
Europe	58.8%	52.6%
United States	17.9%	21.6%
Canada	31.3%	37.8%
Australia/New Zealand	16.6%	50.6%
Asia	0.8%	0.8%
Japan		3.4%

Note: Asia figure includes Japan in 2014, but excludes Japan in 2016.
Source: Global Sustainable Investment Review of 2016.

One of the main motivations for SRI investors is to achieve social change that effectively fits and reflects their personal values and beliefs which brings them pleasure by doing good things (Wallis and Klein, 2015). This kind of financial behavior has a crucial impact on firms' CSR investing strategies. The maturity of SRI from being an option carried out by a small number of investors to a common portfolio adoption for institutional investors has led to the assignment of scores to corporate performers. Companies are ranked according to their "CSR scores" or "CSR rates". To make it comparable across industries and even geographies, these scores are standardized in different dimensions namely environmental, social, and corporate governance performance (ESG). Various socially responsible stock indices, or the so-called CSR indices have been created in accordance with the strong development of SRI. They are, for example, S&P 500 Environmental & Socially Responsible Index (SPXESRP), Dow Jones

Sustainability Index (DJSJ), Calvert Social Index (CSI) or FTSE4GOOD series. Though the selected regions or markets may be different, these indices are all designed to measure the securities performance of companies who meet the common selection criteria of ESG. With the utilization of CSR scores, the contributions of SRIs to the changes in corporate decisions to pick CSR companies are more convenient and transparent.

According to Sparkes and Cowton (2004) and Beal *et al.* (2005) business organization's executives and portfolio managers cannot ignore these potential investors' preferences and expectations. In fact, including CSR activities in corporate agenda may help them create a better stock performance in the market through CSR indices. Kempf and Osthoff (2007) study empirically proved this claim and found an abnormal return of 8.7% a year from SRIs.

This study provides another perspective in analyzing the SRIs by comparing different combinations of ARMA-GARCH's (Autoregressive Moving Average - Generalized Autoregressive Conditional Heteroscedasticity) extended long-memory models. Since the ARCH model's first introduction (Engle, 1982) and its extension GARCH model (Bollerslev, 1986) they have been utilized by numerous studies because they have the ability to model financial time series that commonly exhibit time-varying volatility clustering, which provides a great help in forecasting future movements of investment instruments. This practical application explains why the most popular function of GARCH-family models is to estimate and forecast stock volatilities.

GARCH has various extensions and each of them considers different possible features in the time-series data. This study utilizes the ARFIMA (Autoregressive Fractionally Integrated Moving Average), ARFIMA-GARCH, ARFIMA-FIGARCH (Fractional Integral Autoregressive Conditional Heteroscedasticity) and ARFIMA-HYGARCH (Hyperbolic Generalized Autoregressive Conditional Heteroscedasticity); and according to the literature, there is no consensus on which ARMA-GARCH model provides the best modeling or forecasting performance. According to Sharma (2015), different research with different asset classes in different sample periods, and different evaluation criteria favor different GARCH specifications.

In this paper, the authors focus on one specific aspect of GARCH and its extended models, their capacity to model long-memory dynamics in the volatility, which overcomes the inability to capture long-run positive dependence of the short-memory nature of previous GARCH models. This paper acknowledges this gap by utilizing more developed long-memory GARCH models (i.e., FIGARCH and HYGARCH) to examine the dynamics in returns and volatilities especially for CSR indices, hence, this work particularly focuses on applying different GARCH long-memory models to CSR indices, attempting to study their characteristics as well as to figure out which model performs the best in capturing and forecasting their dynamics.

This study aims to analyze properties of CSR indices related to their returns and volatilities. Particularly, this research focuses on the fractional integration process, which provides clues on the predictability of a particular time-series data (Cheung and Lai, 1995; Bollerslev and Mikkelsen, 1996). The study is motivated by the dearth in literature of studies focusing on CSR indices applying long-memory models. The literature has been generous of studying stock indices while, as far as this paper is concerned, CSR indices have been neglected. This paper acknowledges the growing importance of CSR and SRI, and encourages investors to invest more in this kind of green investments.

This research contributes to the literature by expanding the SRI narrative and moving beyond the question of whether it is a gain or a loss when it comes to SRI investing through studying its time-series data characteristics. The paper examines positive dependence in the returns and volatility of CSR indices from four different markets through the application of four relatively new fractional integration models, namely, ARFIMA, ARFIMA-GARCH, ARFIMA-FIGARCH, and ARFIMA-HYGARCH. This paper's contribution differs from previous studies through the following objectives: a) determine long-memory process in the time-series of CSR; b) look for differences in the characteristics of each market with regards to their short-, intermediate-, and long-memory processes; and lastly, c) challenge the efficient market hypothesis (EMH) of Fama (1970) which poses that stock prices fully reflect information available in the market, making it impossible for investors to earn excess returns by forecasting.

The study attempts to fill the gap in the SRI literature by examining the presence of high-order positive correlations among observations that suggests predictions on future of a CSR index returns is feasible. This topic, to the best of our knowledge, has never been addressed. Findings on the predictability properties of the returns and volatilities of CSR Indices have a huge potential in giving traders access to better investment strategies that may be able to exploit abnormal return opportunities and/or hedge themselves from potential risks inherent in the market. This research provides a valuable knowledge together for SRI investors, which helps them understand better the behavior of CSR index in the long term for better trading decisions. The study can also help investors and fund managers in augmenting their knowledge on some of the technical aspects of CSR indices' time-series.

The paper is structured as follows. Section 1 introduces the paper. Section 2 reviews literature related to GARCH family of long-memory models. Section 3 explains more specific details of the data and methodology. Section 4 shows all the findings together with the analyses and discussions. Finally, Section 5 concludes by summing up all the main findings, explaining implications, and showing some limitations of the study.

2. RELATED LITERATURE

2.1. CSR Initiatives and SRI Performance

In the early years, CSR was viewed to be ideal and only a voluntary behavior for corporations that are willing to protect the welfare of the society. Previous researches have been generous in examining whether there is a financial sacrifice in applying social screenings in selecting portfolio for investment by comparing the performance of SRI funds and conventional funds. Yet, limited attention has been paid in assisting these green investors to make better trading decisions through modelling and forecasting stock returns and volatilities by utilizing proper tools. Tong *et al.* (2016) confirmed that during the recent times, CSR has gained importance and appeared as a necessary dimension of business activities and it has been a critical issue for companies about how to effectively and strategically conduct CSR initiatives. Undoubtedly, one of the main reason is that CSR helps companies build and position their brand image in society as well as in the eyes of shareholders. Furthermore, Ioannou and Serafeim (2015) empirically proved that CSR disclosure helps increase the likelihood of being included in the Dow Jones Sustainable Index, which attracts more socially responsible investors.

The literature is also mixed when it comes to answering the question concerning whether there is a negative trade-off to firms who engage in CSR initiatives or for investors who adopt the SRI philosophy. Opponents of SRI argued that it is costly to have additional monitoring costs and lower portfolio diversification due to limited investment portfolio. For example, some studies found that excluding stocks from companies involving in sin industries such as alcohol, weapons, tobacco, gambling would result in financial loss since these companies are more likely to perform better than "nonsin" companies (Hong and Kacperczyk, 2009; Borgers *et al.*, 2015). Moreover, the study of Kruger (2015) suggested that stock prices exhibit negative reactions to positive CSR news occasionally.

El Ghoul and Karoui (2017) found evidence of a negative relationship between a portfolio CSR scores and its risk-adjusted performance in the sample of 2,168 U.S. equity domestic funds during 2003-2011 period. In other words, CSR level comes at the expense of poorer performance. Likewise, evidence from Gasser *et al.* (2016) on 6,231 international stocks data set found that investors who aimed to achieve optimal portfolios with high social responsibility ratings had to deal with a lower expected returns.

However, a number of studies beg to differ. For example, Lean *et al.* (2015) examined a sample of 500 Europe SRI funds and 248 North American SRI funds (from January 2001 to December 2011) and showed that they outperformed conventional funds. Examining a European data set with ESG ratings, the work of Auer (2016) advocates this point by showing that eliminating unrated stocks provides higher performance than those from traditional portfolios. Furthermore, when applying ESG screens, though environmental and social selection neither provide excess nor loss, governance selection was found to generate additional value.

The study of De and Clayman (2014) also supported this result when suggesting that higher risk-adjusted return stocks usually belonged to high ESG rating group. Lastly, Fulton *et al.* (2012) found 89% of the reviewed studies agreed that high ESG firms outperform the market in the medium- or long-term.

2.2. Long-Memory Process Captured by GARCH Models

Though the improvement in the methods of Baillie *et al.* (1996) for the FIGARCH, and Davidson (2004) for the HYGARCH models have been proven to be useful in capturing the dynamics of stock volatilities, their application in examining the long-memory property of CSR indices is still very limited up to now. It is, nonetheless, necessary to recognize the importance to exploit GARCH models function in analyzing CSR indices as it may encourage SRI investors. The power of the long-memory process in modelling the returns' volatility had been empirically proven by previous researches. For instance, Chkili *et al.* (2014) suggested that commodity markets are best characterized by long-memory models like FIGARCH, FIAPARCH and HYGARCH than short-memory models like GARCH and IGARCH.

Additionally, in investigating the data of carbon, oil, natural gas and coal markets, Liu and Chen (2013) found that FIEC-HYGARCH model was able to capture the long-term volatility behavior in the indices' future returns. Tang and Shieh (2006) also revealed that HYGARCH model outperformed other models in modeling the long-memory characteristic of the Nasdaq 100, S&P 500 and their futures prices. Moreover, the study of volatility in Chinese stock markets by Kang *et al.* (2010) in comparing different GARCH models found that FIGARCH was better equipped to capture the long-memory process in those indices' volatilities. In a more recent study, Malinda and Chen (2016) found that ARFIMA-FIEGARCH has a better performance compared to ARFIMA-HYGARCH in modeling the long-memory dynamics and volatility asymmetry for unrenewable and renewable energy ETFs.

3. DATA AND METHODOLOGY

3.1. Data

This study uses CSR indices collected from the Thomson Reuters/S-Network ESG Best Practices Indices (TRSNESGI)[1]. The Thomson Reuters Corporate, in partnership with the global indices provider S-Network, provides a system of calculating CSR scores/ratings for more than 5,000 companies around the world. The CSR practices of these business organizations are evaluated and ranked in relation to environmental, social and corporate governance performance. The ratings are used for selecting companies to be included in the calculation of the relevant underlying indices from which the final CSR indices are derived from.

Daily closing prices are used to calculate returns for the 16 CSR indices that are under four categories regarding different regional markets, namely US Large Cap (largest capitalization US stocks), ex-US (developed markets except US), Europe and Emerging Markets. The inception dates are of the same period for the first three groups, which is January 2, 2008, however the emerging markets data starts from January 3, 2011 due to limited data availability; and ends until December 13, 2017.

3.2. Methodology

The computation of log returns of CSR indices are as follows:

$$R_{m,t} = \ln\left(\frac{I_t}{I_{t-1}}\right) * 100,$$

[1] *See this link for the details: http://www.tresgindexes.com/*

where $R_{m,t}$ is the CSR index returns at a specific time-series period. This research uses ARFIMA and its joint model with other GARCH-type models, namely ARFIMA-GARCH, ARFIMA-FIGARCH and ARFIMA-HYGARCH to estimate the volatilities of indices. Their models are presented below.

3.2.1. ARFIMA

This Autogressive Fractionally Integrated Moving Average (ARFIMA) was proposed by Granger and Joyeux (1980) with the idea to allow the parameter d to be fractional. The model is defined as below:

$$\phi(L)(1-L)^d(y_t - \mu) = \psi(L)\varepsilon_t$$

in which d represents the fractional integration, L is the lag operator with real number, and ε_t is the innovation term or noise residual.

The fractional differencing lag operator $(1-L)^d$ is obtained in this extended equation:

$$(1-L)^d = 1 - dL + \frac{d(d-1)}{2!}L^2 - \frac{d(d-1)(d-2)}{3!}L^3 + \cdots$$

In this model, if 0<d<5, there is a long memory effect for the stock returns; and when d = 0 a short memory process with the effect of a random shock decays geometrically is exhibited. Noted that when this parameter d = 1, there is the presence of a unit root process. In addition, Hsieh and Lin (2004) showed that there is an intermediate memory when -0.5<d<0, representing that the autocorrelation function decays slower than when it has a short memory. The time series is non-stationary when d≥0.5.

3.2.2. FIGARCH

It is commonly discussed in many literatures that there might be a long memory phenomenon in the time-series data, especially for stocks' volatility. This indicates that if this feature exists, a positive or negative random external shock's effect will make the data react in the same way in the future, therefore, we can tell where it is going (up or down). Considering this factor, FIGARCH model was introduced by Baillie *et al.* (1996) to capture the long memory process. Different from an *I(1)* series with no mean reversion or an *I(0)* with a fast exponential rate of shock decay, this model proposes that a shock to an *I(d)* with 0<d<1 will decay at a slow hyperbolic rate (Tang and Shieh, 2006; Bentes, 2015). With the fractional differencing parameter d in the range from zero to one, FIGARCH allows more flexibility for modeling the persistence of shocks to the conditional variance (Bentes, 2015).

The FIGARCH (p,d,q) model is expressed as below:

$$[\phi(L)(1-L)^d]\varepsilon_t^2 = \omega + [(1-\beta(L)](\varepsilon_t^2 - \sigma_t^2)$$

Where ε_t is the error term or innovation term at time t.

The conditional variance is obtained as:

$$\sigma_t^2 = \omega + \beta\sigma_{t-1}^2 + [1-(1-\beta L)^{-1}(1-\varphi L)(1-L)^d]\varepsilon_t^2$$

The fractional differencing factor is $(1-L)^d$:

$$(1-L)^d = \sum_{k=0}^{\infty}\frac{\Gamma(d+1)L^k}{\Gamma(k+1)\Gamma(d-k+1)}$$

$$= 1 - dL - \frac{1}{2}d(1-d)L^2 - \frac{1}{6}d(1-d)(2-d)L^3 - \cdots$$

$$= 1 - \sum_{k=1}^{\infty} c_k(d) L^k$$

Where $c_1(d) = d, c_2(d) = \frac{1}{2}d(1-d), etc.$

When 0 < d < 1, the series is considered to have long memory dynamics. A short memory process (a shock's effects decay geometrically) is interpreted when d = 0; and a unit root process is exhibited when d = 1.

3.2.3. HYGARCH

Davidson (2004) developed HYGARCH model as a generalization of FIGARCH. He argued that it shows a more genuine long-memory feature than FIGARCH in terms of hyperbolically decaying weights on the square of past shocks (Kwan *et al.*, 2012). The reason is that HYGARCH can overcome the drawback of FIGARCH which is described as "the unexpected behavior of the FIGARCH model may be due less to any inherent paradoxes than to the fact that the unit-amplitude restriction, appropriate to a model of levels, has been transplanted into a model of volatility" (Davidson, 2004). Comparing to IGARCH and FIGARCH, HYGARCH permits the existence of second moments at more extreme amplitudes (Kwan *et al.*, 2012).

The HYGARCH model is defined as:

$$\theta(L) = 1 - \frac{\delta(L)}{\beta(L)}\left(1 + \alpha((1-L)^d - 1)\right) \text{ when } \alpha \geq 0, d \geq 0$$

Provided d > 0:

$$\varsigma = 1 - \frac{\delta(L)}{\beta(L)}(1-\alpha)$$

When d = 1, the equation reduces to:

$$\theta(L) = 1 - \frac{\delta(L)}{\beta(L)}(1 - \alpha L) \qquad and \quad \alpha \geq 0$$

When d is not too large, this model will correspond closely to the case:

$$\theta(L) = 1 - \frac{\delta(L)}{\beta(L)}(1 - \alpha\phi(L))$$

in which

$$\phi(L) = \varsigma(1+d)^{-1} \sum_{j=1}^{\infty} j^{-1-d} L^j$$

And $\varsigma(.)$ is the Riemann Zeta function. Noted that when 0 <d <1, the conditional variance could be considered to exhibit hyperbolic decaying memory (long memory).

4. FINDINGS AND DISCUSSIONS

Table 3 shows the summary statistics of CSR indices. Most of the indices under study started from January 2, 2008, except for the Emerging CSR Markets indices, which started on January 3, 2011. The US Large Cap category posted the only positive returns with an average return of 2.43% among the group of CSR indices, which generally showed negative returns during the chosen study period. This paper posits that SRI investing in the US large capitalization market are more active and mature than their counterparts, thus, they experience steadier flow of investments than the other indices. On the other hand, the European CSR Markets posted the highest average standard deviation with an average of 1.47, while the Emerging CSR Markets have the lowest average at 0.995. All of the CSR indices have negative skewness and leptokurtic distributions. The significant values of the J-Bera statistic indicate that all of their returns are under a non-normal distribution.

Table 4 shows the results of long memory estimation employing ARFIMA and ARFIMA-GARCH models, and applies the minimum value of Akaike Information Criterion (AIC) to identify the best orders of each model with maximum lags of [2,2]. All the d-coefficient values are not significantly different from 0 in the ARFIMA models, but some of them show significant signs in the ARFIMA-GARCH models. The d-coefficients for TRESGUS, TRENVUS, TRCGVUS from the US Large Cap CSR category; and TRSCEU, TRCGVEU from the European CSR category, ranging from -0.188 to -0.059, indicate that they have intermediate memory properties. As a specific example, TRESGUS has a d-coefficient of -0.173 significant at the 10% level with the basic ARCH model at [2,2] and lowest AIC of 2.717. The coefficient implies that the anti-persistence feature exists in the returns of this CSR index. This means that the dependencies among the observations of these CSR indices are weak in the long run. Thus, a short- to medium-term trend reversal could be expected and that the initial data momentum may change sooner than expected. This finding is consistent with the earlier findings by Kang and Yoon (2007) and Diaz and Nguyen (2015) in studying the South Korean stock market and exchange-traded funds (ETFs), respectively. This paper suggests that portfolio managers holding these types of CSR indices should constantly rebalance their portfolio. It is further recommended to not include them as long-term investments, because their return structures are inherently unstable.

Table 5 illustrates the results of the other two more advanced long-memory models, which also applies the minimum value of AIC to identify their best orders. The ARFIMA-FIGARCH models confirm the returns' intermediate memory process in most of those CSR indices mentioned above, namely, TRENVUS and TRCGVUS from the US Large Cap CSR indices; and TRSCEU and TRCGVEU from the European Markets CSR indices. For example, the TRENVUS d-coefficient is -0.168 significant at the 10% level with the basic ARCH model at [2,2] and lowest AIC of 2.711. The results of the ARFIMA-HYGARCH models, on the other hand, are almost the same, with the addition of TRESGUS, which has a d-coefficient of -0.172 significant at the 10% level with the basic ARCH model at [1,2] and lowest AIC of 2.710. These significant negative coefficients in the returns again imply that the anti-persistence feature exists in the returns of these CSR indices. These findings are consistent with the previous papers of Korkmaz *et al.* (2009) and Tan and Khan (2010) in studying the Turkish and Malaysian stock markets, respectively.

Regarding the FIGARCH volatility d-coefficients, most of the CSR indices exhibit long-memory dynamics with values ranging at $0<d<1$, except for TRESGEX and TRSCEX of the Emerging Markets CSR indices. As a sample result, TRENVUS, which has a d-coefficient of 0.495 significant at the 1% level with the basic ARCH model at [2,2] and lowest AIC of 2.711. The presence of long-memory in the volatility implies that there is a strong positive dependence among observations, and thus, a predictable structure in volatility exists. This finding is useful for investors in monitoring the risk of their portfolios, and in making long-term investment decisions. The ARFIMA-HYGARCH models, on the other hand, strongly confirms these initial results, and showed all significant findings. For reference, TRSCUS of the US Large Cap CSR indices has a d-coefficient of 0.582 significant at the 1% level with the basic ARCH model at [1,2] and lowest AIC of 2.732. This HYGARCH model confirms the initial findings of the FIGARCH in determining the presence of long-memory process in the volatility. However, the insignificant log-alphas, which is supposed to be a unique of the HYGARCH model over the other long-memory, possibly suggests that the model can nest on its predecessor, the earlier FIGARCH model

Table-3. Descriptive statistics of CSR indices returns.

	CSR Indices	Start of Data	Daily	Returns	Std. Dev.	Skew.	Kurt.	J-Bera
US Large Cap								
1	TRESGUS - Thomson Reuters/S-Network ESG Best Practices US Large Cap ESG Index	Jan. 2, 2008	2588	0.024	1.285	-0.352	10.467	11868*** (0.000)
2	TRENVUS - The Thomson Reuters/S-Network ESG Best Practices US Large Cap Environmental Index	Jan. 2, 2008	2589	0.024	1.285	-0.379	10.699	12411*** (0.000)
3	TRSCUS - The Thomson Reuters/S-Network ESG Best Practices US Large Cap Social Index	Jan. 2, 2008	2589	0.024	1.304	-0.376	10.595	12171*** (0.000)
4	TRCGVUS - The Thomson Reuters/S-Network ESG Best Practices US Large Cap Governance Index	Jan. 2, 2008	2589	0.025	1.272	-0.338	10.427	11778*** (0.000)
Ex-US Developed Markets								
5	TRESGDX - Thomson Reuters/S-Network ESG Best Practices Developed Markets (ex-US) ESG Index	Jan. 2, 2008	3401	-0.003	1.109	-0.360	12.291	21481*** (0.000)
6	TRENVDX - The Thomson Reuters/S-Network ESG Best Practices Developed Markets (ex-US) Environmental Index	Jan. 2, 2008	3480	-0.003	1.041	-0.376	12.565	22973*** (0.000)
7	TRSCDX - The Thomson Reuters/S-Network ESG Best Practices Developed Markets (ex-US) Social Index	Jan. 2, 2008	3480	-0.002	1.060	-0.367	12.135	21429*** (0.000)
8	TRCGVDX - The Thomson Reuters/S-Network ESG Best Practices Developed Markets (ex-US) Governance Index	Jan. 2, 2008	3480	-0.003	1.123	-0.386	13.304	25751*** (0.000)
European Markets								
9	TRESGEU - Thomson Reuters/S-Network ESG Best Practices Europe ESG Index	Jan. 2, 2008	3498	-0.004	1.311	-0.147	11.847	20467*** (0.000)
10	TRENVEU - The Thomson Reuters/S-Network ESG Best Practices Europe Markets Environmental Index	Jan. 2, 2008	2595	-0.005	1.532	-0.089	7.4577	6017*** (0.000)
11	TRSCEU - The Thomson Reuters/S-Network ESG Best Practices Europe Markets Social Index	Jan. 2, 2008	2595	-0.006	1.526	-0.110	7.294	5757.6*** (0.000)
12	TRCGVEU - The Thomson Reuters/S-Network ESG Best Practices Europe Markets Governance Index	Jan. 2, 2008	2594	-0.005	1.502	-0.151	8.639	8076.9*** (0.000)
Emerging Markets								
13	TRESGEX - Thomson Reuters/S-Network Emerging Markets ESG Best Practices Index	Jan. 3, 2011	1810	-0.004	0.997	-0.340	3.311	861.43*** (0.000)
14	TRENVEX - Thomson Reuters/S-Network Emerging Markets Environmental Best Practices Index	Jan. 3, 2011	1811	-0.006	1.011	-0.378	3.278	853.55*** (0.000)
15	TRSCEX - Thomson Reuters/S-Network Emerging Markets Social Best Practices Index	Jan. 3, 2011	1811	-0.007	0.975	-0.353	3.373	896.16*** (0.000)
16	TRCGVEX - Thomson Reuters/S-Network Emerging Markets Governance Best Practices Index	Jan. 3, 2011	1811	-0.003	0.997	-0.348	3.397	907.28*** (0.000)

Note: *, ** and *** are significance at 10, 5 and 1% levels, respectively; p-values are in parentheses.

Table-4. Long-memory estimation results for ARFIMA, ARFIMA-GARCH models.

Indices	ARFIMA				ARFIMA-GARCH			
	d-coeff.	ARMA	AIC	Log-Likelihood	d-coeff.	ARCH	AIC	Log-Likelihood
US Large Cap								
TRESGUS	0.008 (0.943)	(1,1)	3.330	-4304.244	-0.173* (0.089)	(2,2)	2.717	-3507.219
TRENVUS	0.009 (0.935)	(1,1)	3.331	-4306.888	-0.179* (0.056)	(2,2)	2.717	-3508.020
TRSCUS	0.014 (0.903)	(1,1)	3.360	-4344.156	-0.172 (0.106)	(2,2)	2.740	-3537.461
TRCGVUS	0.003 (0.980)	(1,1)	3.310	-4279.877	-0.188** (0.030)	(2,2)	2.703	-3489.414
Ex-US Developed Markets								
TRESGDX	0.082 (0.583)	(1,2)	3.031	-5148.432	-0.046 (0.569)	(1,1)	2.593	-4402.024
TRENVDX	-0.017 (0.772)	(1,1)	2.910	-5052.534	-0.033 (0.448)	(2,1)	2.501	-4343.157
TRSCDX	0.066 (0.659)	(1,2)	2.942	-5113.631	-0.029 (0.401)	(1,1)	2.525	-4386.163
TRCGVDX	-0.037 (0.511)	(1,0)	3.062	-5324.314	-0.031 (0.315)	(2,2)	2.606	-4526.157
European Markets								
TRESGEU	-0.023 (0.468)	(2,2)	3.380	-5904.443	-0.022 (0.190)	(2,2)	2.971	-5186.026
TRENVEU	0.097 (0.516)	(1,2)	3.691	-4782.736	-0.059 (0.105)	(2,1)	3.243	-4198.546
TRSCEU	0.097 (0.511)	(1,2)	3.682	-4771.111	-0.059* (0.095)	(2,1)	3.237	-4191.597
TRCGVEU	0.097 (0.540)	(1,2)	3.649	-4726.803	-0.082** (0.043)	(2,1)	3.168	-4100.089
Emerging Markets								
TRESGEX	-0.081 (0.124)	(1,0)	2.786	-2517.378	-0.064 (0.139)	(1,1)	2.622	-2366.986
TRENVEX	-0.070 (0.181)	(1,0)	2.817	-2546.652	-0.051 (0.226)	(1,1)	2.658	-2400.452
TRSCEX	-0.074 (0.158)	(1,0)	2.740	-2476.780	-0.050 (0.233)	(1,1)	2.575	-2325.450
TRCGVEX	-0.078 (0.165)	(1,0)	2.786	-2518.614	-0.062 (0.149)	(1,1)	2.609	-2356.411

Note: *, ** and *** are significance at 10, 5 and 1% levels, respectively; p-values are in parentheses.

Table-5. Long memory estimation results for ARFIMA-FIGARCH, ARFIMA-HYGARCH models.

	ARFIMA-FIGARCH					ARFIMA-HYGARCH					
	d-coeff. (Arfima)	ARCH	d-coeff. (Figarch)	AIC	Log-Likelihood	d-coeff. (Arfima)	ARCH	d-coeff. (Figarch)	AIC	Log Alpha	Log-Likelihood
US Large Cap											
TRESGUS	-0.162 (0.123)	(1,1)	0.493*** (0.000)	2.711	-3499.587	-0.172 (0.060)*	(1,2)	0.576*** (0.000)	2.710	-0.041 (0.137)	-3496.764
TRENVUS	-0.168* (0.066)	(2,2)	0.495*** (0.000)	2.711	-3499.881	-0.176** (0.041)	(1,2)	0.572*** (0.000)	2.709	-0.042 (0.135)	-3497.253
TRSCUS	-0.169 (0.073)*	(1,2)	0.533*** (0.000)	2.733	-3529.108	-0.170 (0.080)*	(1,2)	0.582*** (0.000)	2.732	-0.041 (0.127)	-3527.209
TRCGVUS	-0.178** (0.029)	(1,2)	0.499*** (0.000)	2.696	-3482.247	-0.185** (0.022)	(1,2)	0.581*** (0.000)	2.695	-0.043 (0.121)	-3479.256
Ex-US Developed Markets											
TRESGDX	-0.054 (0.349)	(2,2)	0.451*** (0.001)	2.585	-4384.145	-0.054 (0.350)	(2,2)	0.457** (0.013)	2.585	-0.003 (0.943)	-4384.137
TRENVDX	-0.032 (0.487)	(2,2)	0.385*** (0.000)	2.492	-4325.706	-0.032 (0.500)	(2,2)	0.365** (0.019)	2.492	0.016 (0.853)	-4325.621
TRSCDX	-0.046 (0.451)	(2,1)	0.523*** (0.000)	2.516	-4368.085	-0.046 (0.456)	(2,1)	0.545*** (0.000)	2.517	-0.011 (0.631)	-4367.843
TRCGVDX	-0.030 (0.321)	(2,1)	0.543*** (0.000)	2.595	-4507.496	-0.030 (0.326)	(2,1)	0.558*** (0.000)	2.596	-0.008 (0.720)	-4507.356
European Markets											
TRESGEU	-0.063 (0.230)	(2,2)	0.362*** (0.000)	2.955	-5156.705	-0.063 (0.238)	(2,2)	0.310*** (0.000)	2.955	0.073 (0.303)	-5154.951
TRENVEU	-0.060* (0.072)	(2,2)	0.392*** (0.000)	3.231	-4181.298	-0.060*** (0.006)	(2,2)	0.334*** (0.000)	3.231	0.069 (0.286)	-4180.149
TRSCEU	-0.060 (0.062)*	(2,2)	0.389*** (0.000)	3.224	-4172.534	-0.060* (0.059)	(2,2)	0.337*** (0.000)	3.224	0.065 (0.290)	-4171.421
TRCGVEU	-0.083 (0.090)*	(2,2)	0.397*** (0.000)	3.156	-4082.540	-0.083* (0.088)	(2,2)	0.354*** (0.000)	3.156	0.048 (0.380)	-4081.874
Emerging Markets											
TRESGEX	-0.067 (0.118)	(2,1)	0.639 (0.123)	2.623	-2365.409	-0.067 (0.125)	(2,1)	0.882*** (0.000)	2.622	-0.012 (0.296)	-2364.249
TRENVEX	-0.053 (0.200)	(2,1)	0.658** (0.036)	2.658	-2398.465	-0.054 (0.205)	(2,1)	0.869*** (0.000)	2.657	-0.013 (0.269)	-2397.356
TRSCEX	-0.050 (0.228)	(2,1)	0.533 (0.111)	2.576	-2324.715	-0.051 (0.226)	(2,1)	0.907*** (0.000)	2.576	-0.014 (0.238)	-2323.161
TRCGVEX	-0.066 (0.119)	(2,1)	0.717** (0.040)	2.610	-2355.527	-0.066 (0.131)	(2,1)	0.865*** (0.000)	2.610	-0.013 (0.246)	-2354.216

Note: *, ** and *** are significance at 10, 5 and 1% levels, respectively; p-values are in parentheses.

This means that the FIGARCH and HYGARCH models can be treated in the same respect without using any other performance metrics. However, this study utilized the highest number of log-likelihood value to determine the best fitting model for the CSR indices.

This study shows that the combined models of ARFIMA-HYGARCH are the superior methods over ARFIMA, ARFIMA-GARCH and ARFIMA-FIGARCH in determining positive dependence among CSR indices. For example, TRSCEU of the European Markets CSR index, which is significant among the three volatility models of GARCH, FIGARCH and HYGARCH has the highest log-likelihood value in ARFIMA-HYGARCH models of -4171.421 compared to the -4172.534 of ARFIMA-FIGARCH, and -4191.597 of ARFIMA-GARCH. The power of the more advanced fractional integration model HYGARCH is consistent among the earlier findings of Tang and Shieh (2006) and Chikhi *et al.* (2012) where they also proved that HYGARCH performs better than other models in estimating long-memory dynamics of S&P500, Nasdaq100 and DowJones indices; and Korean exchange rate, respectively.

This study also noticed that as the volatility model progresses from GARCH to FIGARCH to HYGARCH, the log-likelihood values consistently goes up. This shows that the iterations of the HYGARCH are superior over its fractional integration model predecessors. This feature in volatility suggests a presence of strong persistence and therefore, investors may earn more profits by keeping their investments in long term with proper forecasting tools. Overall, the evidence of long-memory effect in CSR indices' volatilities is strong in all four market groups. This is not consistent with the EMH (Fama, 1970) because the study's findings suggest that the volatility has a predictable structure. This also means that price movements do not effectively reflect all the information in the market, thus, can still cause abnormal returns.

5. CONCLUSIONS AND LIMITATIONS

This study focused on identifying return and volatility characteristics of CSR indices using the four models of ARFIMA, ARFIMA-GARCH, ARFIMA-FIGARCH and ARFIMA-HYGARCH. This paper analyzed short-, medium-, and long-memory processes in the time-series of US Large Cap, Ex-US Developed, European and Emerging Markets. According to the results, intermediate memory property is evident in the returns of US Large Cap and European Markets CSR indices, which implies that the dependencies among the observations of these CSR indices are weak in the long run. This study advised that traders and portfolio should not hold these specific indices in the long haul for they have fluctuating return outcomes. One consistent finding of this paper was the consistent display of positive dependence in the volatilities of CSR indices, which implied strong volatility persistence in the long term. In line with this, this paper suggested that investors can use these predictable volatility structure to earn excess returns by increasing exposure to lower than average CSR volatility, and lessening exposure to higher than average volatility periods. Moreover, in comparing among these models, ARFIMA-HYGARCH consistently was the best fitting model to estimate long-memory effects in volatility with the highest log-likelihood values.

Given the above findings, the paper is not without its shortcomings. First, the relatively new long-memory model HYGARCH still has limited utilization in academic research, thus, creating a more solid discussion and connection with the previous literature is limited. Second, since most CSR indices are of recent inceptions, the short timeline restricted the paper in considering structural break tests. Lastly, this study only utilized the FIGARCH and HYGARCH models, it is suggested that future researches use other fractionally integrated models (i.e., FIAPARCH and FIEGARCH) in analysing CSR indices. Despite these limitations, the current study still has its own merits and has considerable contribution to the literature of SRI or impact investing. Investors may be able to make better decisions in their trading strategies, i.e. asset/portfolio allocation and optimization. The findings provide a means to manage risks by helping measure potential future losses from too much volatility with proper models developed using historical data.

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