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Long Memory and Shifts in the Returns Of Green and Non-Green Exchange-Traded Funds (ETFs)

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ABSTRACT : *This study using the ARFIMA-FIGARCH models found no significant long-memory process among Green ETFs. However, there is a presence of long memory attributes in the volatilities for Non-Green ETFs. For most of the results, this research failed to reject the efficient market hypothesis, and findings of non-stationarity and non-invertibility properties can provide a warning for investors to not rely heavily on their numerical predictions and not always think green with these investment instruments.*

KEYWORDS: *Long-memory properties, ARFIMA-FIGARCH models, Green and Non-green ETFs*

I. INTRODUCTION

Exchange-traded funds (ETFs) have extended into sectors, international markets, fixed income, bonds, commodities, and currency, since its creation in 1989. The boom in US-based ETFs have already reached a total of $814.6 billion in assets after the 1st half of 2010 according to investment firm BlackRock, and clean and green ETFs is one of the fastest growing segment. Based on ETF database website, since 2005, funds poured in clean energy increased by 230% to $162 billion in 2009, and the US has invested $18.6 billion. With the growing concerns on climate change and discoveries of new technologies with more resourceful extraction of energy from natural resources, channeling of funds on Green ETFs will help overcome our dependence on non-renewable sources that sacrifices the environment.

This research has two main propositions. First, we want to examine if there's also long-memory present in Green ETFs given its aim of sustainability, in contrast with Non-green ETFs. Long-memory properties will be examined in both ETF returns and volatilities, like what Kang & Yoon (2007) and Tan & Khan (2010) discovered for stock returns. Second, this paper will test the efficient market hypothesis (EMH) suggesting that returns have a random walk of Fama (1970) for ETFs. To investigate these hypotheses, this study utilizes the fractionally integrated autoregressive moving average (ARFIMA) processes first appeared in the papers of Granger & Joyeux (1980) and Hosking (1981), wherein the difference parameter is allowed to be a non-integer; and the fractional integrated general autoregressive conditional heteroskedasticity (FIGARCH) model to verify long memory in return volatility as suggested by Baillie et al. (1996).

In the literature, ARFIMA-FIGARCH models have been applied to stock market returns (e.g., Floros, et al., 2007; Kang & Yoon, 2007; McMillan & Thupayagale, 2008; Korkmaz et al., 2009 and Tan & Khan, 2010), exchange rates (e.g., Beine et al., 2002) and commodities (e.g., Choi & Hammoudeh, 2009). This paper aims to contribute to the literature on ETFs. To the best of our knowledge no formal empirical study yet has examined the long-memory of their returns and volatilities using ARFIMA-FIGARCH models. By comparing Green ETFs and Non-Green ETFs we can delineate if these two opposite forces in the ETFs market also have opposite findings. Looking at the existence of short, intermediate and long memories in these ETFs can strengthen or weaken fund managers' projection of the viability of Green and Non-green ETFs as alternative investments. The research is written as follows. Section II explains the data and ARFIMA-FIGARCH models; Section III elaborates the empirical results; and Section IV presents the conclusion.

II. DATA AND METHODOLOGY

Daily closing prices of Green and Non-Green ETFs obtained from the Yahoo! Finance Web site are used in this research. The study period begins at the varying inception dates of the ETFs. This study initially collected data from thirteen Green and thirteen Non-Green ETFs. Five Green ETFs with the lowest capitalizations were removed, and the remaining 8 were further trimmed down to five by selecting the sectors that are most actively traded, water and clean energy. On the other hand, six Non-green ETFs were eliminated because of serial correlation problems, and the remaining seven were also cut down to five to balance the data; they represent mining and non-renewable energy.

The ARFIMA model is a parametric approach in econometric time-series to examine long-memory characteristics (Granger & Joyeux, 1980; and Hosking, 1981). This model allows the difference parameter to be a non-integer and consider the fractionally integrated process $I(d)$ in the conditional mean. The ARFIMA (p,d,q) model can be written as:

$$\Phi(L)(1-L)^d Y_t = \Theta(L)\varepsilon_t, \varepsilon_t \sim (0, \sigma_\varepsilon^2), \quad (1)$$

where *d* represents the fractional integration real number parameter, L denotes the lag operator and ε_t is a white noise residual. The equation satisfies both stationarity and invariability conditions.

The fractional differencing lag operator $(1-L)^d$ can be characterized by the following expanded equation:

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

When the ARFIMA model is $-0.5 < d < 0.5$, the process is stationary where the effect of shocks to ε_t decays at a gradual rate to zero. If $d = 0$, the process demonstrates short memory and the effect of shocks decays geometrically. When $d = 1$, there is a unit root process. For $0 < d < 0.5$, there is a long memory or positive dependence among distant observations. If $-0.5 < d < 0$ there is the presence of intermediate memory or antipersistence (Baillie et al., 1996). When $d \geq 0.5$, the process is non-stationary, while $d \leq -0.5$ is a stationary, but noninvertible process, which means that the sequence cannot be represented by any autoregressive model. The FIGARCH model as proposed by Baillie et al. (1996) captures long memory in return volatility. The model gives more adaptability in modeling the conditional variance, covering the covariance stationary GARCH for $\bar{d}=0$, and the non-stationary IGARCH for $\bar{d}=1$. The FIGARCH $(p,\bar{d},q)$ model is expressed as:

$$\phi(L)(1-L)^{\bar{d}}\varepsilon_t^2 = \omega + [1-\beta(L)]v_t, \quad (3)$$

where v_t is the innovation for the conditional variance, and the root of $\phi(L)$ and $[1-\beta(L)]$ lie outside the unit root circle.

The ARFIMA-FIGARCH models detects the predictability of ETF returns and volatilities, thus, the presence of the *d* parameter lying inside this range $0 < d < 1$ or a presence of positive dependence in the structure easily rejects the EMH hypothesis of Fama (1970). However, findings outside of this range support non-stationarity and non-invertibility of return series and conclude that Green and Non-green ETFs don't have predictable structures, thus, stochastic property.

III. EMPIRICAL RESULTS

Table 1 illustrates that Green ETFs mostly have positive average returns, except for PHO; and all Non-green ETFs have negative average returns. Non-green ETFs generally has higher volatility compared to Green ETFs. Most of the samples are positively skewed except for GDX and PKOL, both are Non-green ETFs, and the kurtosis coefficients have a leptokurtic distribution. The Jarque-Bera statistic for residual normality shows that the ETF returns are under a non-normal distribution assumption. All samples have no serial correlation as shown by the Q correlation coefficient. To identify the orders of ARFIMA and FIGARCH models, this paper applied the minimum value of the Akaike Information Criterion (AIC). This research used the Lagrange Multiplier Test (ARCH-LM) to test the ARCH effect and the null hypothesis for all samples was rejected, which means that we can apply GARCH models in the chosen ETFs. Table 2 presents the results for both ARFIMA and ARFIMA-FIGARCH models. ARFIMA model identified three significant results. The returns of PHO, CGW and GDX exhibit intermediate memory process, which means that positive or negative trends in a particular time are weak, and will more likely change its course in the next trading days. This should serve as a warning sign for investors not to keep investments in the long-run. The XME ETF showed a long-memory process, consistent with the findings of Nouira et al. (2004), Floros et al. (2007), Kang & Yoon (2007), Choi & Hammoudeh (2009) and Tan & Khan (2010). This means that returns of SPDR S&P Metals and Mining ETF can be predicted, because dependence between distant observations is evident. Fund managers and investors can be able to exploit this result by having a position on XME. The combined ARFIMA-FIGARCH models proved that most Green ETFs' returns have intermediate memory process with significant results from PHO, CGW, PIO and TAN ETFs. While, non-green ETFs only has one significant result, GDX, but also demonstrates the same anti-persistence process. Traders trying to model and forecast the following ETFs would find it difficult to earn extra returns, because their structures are inherently unstable.

Table 1: The Sample Size and Period of Green and Non-green ETFs

Indices and Green ETFs	Inception	Obs.	Mean	Std. Dev.	Skew.	Kurt.	J-Bera	Q(10)
PowerShares Water Resources (PHO)	12/6/2005	1265	-0.007	0.838	0.125	5.486	1589.8***	7.306
Claymore S&P Global Water (CGW)	5/14/2007	919	0.008	0.866	0.362	7.266	2041.8***	11.688
Market Vectors Alternative Energy (GEX)	5/3/2007	922	0.032	1.378	0.408	5.809	1321.9***	12.771
PowerShares Global Water (PIO)	6/13/2007	898	0.011	0.915	0.010	8.288	2570.2***	10.7523
Claymore/MAC Global Solar Energy (TAN)	4/15/2008	687	0.079	1.805	0.479	4.675	651.75***	10.856
Indices and Non-Green ETFs	**Period**	**Obs.**	**Mean**	**Std. Dev.**	**Skew.**	**Kurt.**	**J-Bera**	**Q(10)**
iShares Silver Trust (SLV)	4/28/2006	1179	-0.027	1.0411	1.005	7.115	2685.0***	5.220
Market Vectors Gold Miners (GDX)	5/22/2006	1164	-0.019	1.333	-0.140	6.531	2072.2***	16.867
SPDR Metals and Mining (XME)	6/22/2006	1128	-0.015	1.421	0.539	4.321	932.26***	7.500
PowerShares DB Silver (DBS)	1/5/2007	1007	-0.033	1.063	1.104	10.522	4895.5***	9.561
Global Coal Portfolio (PKOL)	9/18/2008	575	-0.034	1.5361	-0.422	5.699	795.05***	29.523

Source: Yahoo Finance – various inception dates up to December 13, 2010; http://www.yahoo.com/finance.

Table 2: Summary Statistics of ARFIMA and ARFIMA-FIGARCH models

Green ETFs	ARFIMA			ARCH-LM	ARFIMA-FIGARCH			
	model	d-coeff.	AIC		d-coeff.	model	d-coeff.	AIC
PHO	(3,3)	-0.050* (0.082)	2.480	89.266***	-0.157** (0.019)	(3,2)	0.673*** (0.000)	2.030
CGW	(2,3)	-0.066* (0.100)	2.544	41.751***	-0.140*** (0.006)	(1,1)	0.710*** (0.000)	2.088
GEX	(0,1)	-0.032 (0.438)	3.486	73.033***	-0.030 (0.520)	(1,0)	0.842*** (0.000)	2.970
PIO	(2,2)	-0.014 (0.613)	2.663	28.321***	-0.101** (0.039)	(3,2)	0.704*** (0.000)	2.222
TAN	(2,3)	-0.044 (0.313)	4.021	31.865***	-0.260* (0.100)	(2,1)	0.913*** (0.010)	3.580
Non-Green ETFs	**ARFIMA**			**ARCH-LM**	**ARFIMA-FIGARCH**			
	model	**d-coeff.**	**AIC**		**d-coeff.**	**model**	**d-coeff.**	**AIC**
SLV	(1,0)	-0.023 (0.547)	2.925	8.634***	-0.063 (0.338)	(3,3)	0.355** (0.033)	2.728
GDX	(2,3)	-0.159* (0.078)	3.413	25.990***	-0.432*** (0.004)	(3,2)	0.701** (0.050)	3.067
XME	(3,3)	0.186* (0.051)	3.543	65.517***	-0.161 (0.285)	(2,1)	0.869*** (0.002)	3.177
DBS	(3,3)	-0.016 (0.167)	3.665	7.9291***	-0.128 (0.235)	(3,2)	0.426** (0.013)	3.205
PKOL	(2,1)	-0.078 (0.261)	3.700	15.617***	-0.153 (0.119)	(1,0)	0.430*** (0.002)	3.295

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

For the return volatility outcomes, all of the Green ETFs and Non-green ETFs under study showed long-memory processes in their volatilities, in-line with the findings of Kang & Yoon (2007), McMillan & Thupayagale (2008), and Choi & Hammoudeh (2009). These results indicate that volatilities of these ETFs have predictable structures, and given the right modeling and forecasting methods, investors can be able to benefit from them. Long memory in returns and volatilities exist from the samples, making us conclude that the weak form efficient market hypothesis of Fama (1970) may not be suitable with this type of investment instruments. A possible evidence dual long memory process might be present with XME ETF using ARFIMA and ARFIMA-FIGARCH models. This is consistent with the earlier findings of Kang & Yoon (2007) and Tan & Khan (2010). As per our recent conclusions, proponents of Green ETFs cannot expect these channels to be in contrast with Non-green ETFs because similar properties rose from our findings.

IV. CONCLUSION

Sustainability is at the core of investing for the environment, wherein the money invested today is believed to have a strong connection with its long-term gains. This study using the ARFIMA-FIGARCH models found significant long-memory processes in the volatilities Green and Non-green ETFs, which means that there is a possibility that they can be forecasted, making traders gain extra profits by making the right model and prediction, particularly with SPDR S&P Metals and Mining (ticker: XME) having dual long-memory properties. For most of the results, this research may possibly reject the weak-form efficient market hypothesis of Fama (1970), because of the presence of long memory processes. Findings also provide a warning for fund managers and investors to not rely heavily on their numerical predictions with these investment instruments, because of their intrinsic unstable structures with the presence of anti-persistent tendencies in returns.

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