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Long-Memory Modeling and Forecasting of High-Carbon Intensity Rating Exchange-Traded Funds (ETFs)

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Abstract: This paper offers statistical insights into the predictability of returns and volatility for exchange-traded funds (ETFs) with low- to high-carbon intensities, utilizing three configurations of long-memory models: autoregressive fractionally integrated moving average (ARFIMA) combined with generalized autoregressive conditional heteroskedasticity (GARCH), ARFIMA integrated with fractionally integrated GARCH, and ARFIMA paired with hyperbolic GARCH. The findings reveal that high-carbon intensity ETFs generally yield higher positive returns and exhibit decreased volatility than their low-carbon intensity counterparts. Additionally, the study identifies volatility clustering, where lagged conditional variances exert a greater influence than significant lagged mean returns. The analysis also demonstrates the presence of positive long-term dependence in the time series of several high- and low-carbon intensity ETFs, indicating that forecasting using fractionally integrated models is feasible. However, the results suggest no definitive differences in the characteristics of high- and low-carbon intensity ETFs concerning short-term, intermediate-term, and long-term memory processes, as some ETF datasets yielded insignificant findings. Notably, the papers observe anti-persistent characteristics, which caution investors against holding these ETFs for extended periods or relying heavily on current trends for decision-making.

Keywords: high-carbon intensity and low-carbon intensity ETFs, long-memory models, anti-persistent properties

1. Introduction

The urgency to mitigate climate change has spurred significant shifts in global capital allocation. Governments, investors, and corporations are redirecting capital toward activities and technologies that lower greenhouse gas (GHG) emissions and enhance climate resilience. This transition aligns with the Paris Agreement's goals and the broader objective of achieving a low-carbon economy. Finance has taken center stage in this endeavor, not only as a conduit for allocating resources but also as a mechanism for influencing corporate behavior and fostering sustainable growth. As sustainable finance gains traction, investors are increasingly aligning portfolios with environmental objectives, often by reducing exposure to fossil fuel-intensive sectors. This trend is driven by both financial considerations—such as climate risk, stranded asset concerns, and regulatory shifts—and ethical imperatives rooted in climate justice and environmental stewardship.

Yet this divestment movement is not without contention. Critics argue that reallocating away from fossil fuel assets may undermine portfolio returns or disrupt market stability. On the other hand, proponents view divestment as a lever for reshaping industrial behavior and accelerating the energy transition. The financial markets have begun to internalize these climate-related risks and opportunities. Notable contributions, such as [1], document how transition risks are increasingly priced into asset valuations. Complementarily, [2] advocate incorporating carbon intensity into corporate and fund rankings to better reflect firms' environmental performance. These developments underscore a vital research question: how do carbon-related attributes influence financial instruments, particularly in the context of market efficiency and return predictability?

Within this broader climate–finance nexus, exchange-traded funds (ETFs) emerge as critical yet underexplored vehicles. ETFs play a growing role in portfolio construction due to their low costs, diversification features, and passive management structure. With assets under management in ETFs surpassing trillions globally, they reflect both market sentiment and investment strategies. Despite this, academic inquiry into the carbon characteristics of ETFs—especially those classified as carbon-intensive—remains sparse. Most empirical studies have focused on individual stocks, mutual funds, or corporate emissions, leaving a significant research gap in understanding how ETFs exposed to high-emitting sectors behave over time. Reference [3] highlights the strategic relevance of ETFs in passive investment paradigms, yet their environmental footprint,

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volatility patterns, and return predictability remain insufficiently understood.

Addressing this gap, this study focuses on carbon-intensive ETFs, particularly their long-memory behavior—a statistical property that captures the degree of persistence or anti-persistence in time-series data. In doing so, the study bridges two important domains: environmental finance and advanced time-series modeling. While prior work has explored the implications of carbon intensity on firm valuation or mutual fund flows, little is known about how such intensity influences the temporal dynamics of ETF returns and volatility. This omission is striking given that carbon-intensive ETFs represent a substantial pool of assets and may serve as proxies for sectoral performance in energy, utilities, or industrials.

To fill this research void, the study applies fractional integration (FI) models to investigate the long-memory properties of carbon-intensive ETFs. Unlike traditional short-memory models such as Autoregressive Integrated Moving Average (ARIMA) or generalized autoregressive conditional heteroskedasticity (GARCH), FI models offer a more flexible framework by allowing the differencing parameter to take fractional values. This enables the detection of subtle and persistent patterns in financial time-series data, which are often missed by classical models. As emphasized by [4], FI provides a robust mechanism to assess persistence and mean reversion using US real economic activity. The present study advances this line of inquiry by applying three integrated model combinations: (a) autoregressive fractionally integrated moving average (ARFIMA) combined with GARCH (ARFIMA-GARCH), (b) ARFIMA integrated with fractionally integrated GARCH (ARFIMA-FIGARCH), and (c) ARFIMA paired with hyperbolic GARCH (ARFIMA-HYGARCH). The inclusion of HYGARCH, following [5], is particularly novel in this context, given its ability to capture both long memory in mean and volatility with hyperbolic decay structures.

This approach has strong theoretical and practical implications. From a theoretical standpoint, the research challenges the efficient market hypothesis, which posits that price movements are random and devoid of predictable structure. If long-memory characteristics are detected, especially in carbon-intensive ETFs, it would suggest that past information has persistent effects—offering scope for forecasting and potentially generating abnormal returns. Practically, the findings have implications for portfolio managers, environmental, social, and governance (ESG) investors, and policymakers. By modeling volatility clustering and return persistence, this study provides insights into the risk-return profile of carbon-intensive ETFs, informing better asset allocation and sustainability-focused investment strategies.

The study is guided by four research objectives:

1) To investigate the presence of dual long-memory processes—affecting both returns and volatility—in carbon-intensive ETFs, thereby testing the weak-form market efficiency.
2) To identify volatility clustering in high- and low-carbon intensity ETFs, as a signal of persistent risk factors influenced by carbon exposure.
3) To examine the differences in short-, intermediate-, and long-memory characteristics between high- and low-carbon intensity ETFs, shedding light on the structural behavior of carbon-linked portfolios.
4) To determine the best-fitting FI model combinations using log-likelihood and other performance criteria, offering methodological guidance for future research in sustainable finance.

This study makes three unique contributions to the literature. First, it pioneers the application of combined ARFIMA-GARCH, ARFIMA-FIGARCH, and ARFIMA-HYGARCH models in the context of carbon-intensive ETFs—an area previously unexamined. Second, it enriches the theoretical understanding of how environmental characteristics like carbon intensity shape the statistical properties of financial assets. Third, it offers actionable insights for asset managers and policymakers concerned with climate-aligned investment performance and risk mitigation.

By situating carbon-intensive ETFs within a rigorous long-memory framework, this research pushes the frontier of sustainable finance beyond static ESG scores or carbon disclosures. Instead, it delves into the dynamic behavior of market instruments in the context of climate risk, offering a new lens to understand the temporal structure of returns in the green transition era. In doing so, it underscores the importance of developing tools that are both environmentally and statistically sophisticated—ensuring that sustainability considerations are integrated not only at the level of policy and ethics but also within the mechanics of financial modeling.

2. Literature Review

The modeling of long-memory properties in financial time-series data has garnered increasing scholarly attention, particularly in the context of ESG-oriented investments. FI models, such as ARFIMA, have proven effective in identifying persistent dependence in asset returns. However, scholars have pointed out the limitations of ARFIMA-GARCH models in fully capturing volatility dynamics, especially in assets characterized by high environmental risk exposure [6]. As [7] suggest, volatility is increasingly influenced by firms' ESG performance, particularly carbon-related disclosures. Firms with low ESG ratings tend to exhibit greater volatility and higher risk premiums, raising important implications for portfolio construction.

The application of long-memory models to ESG-focused investments has evolved alongside an increasing recognition of carbon intensity as a material financial risk. Firms with high GHG emissions offer excess returns—a phenomenon known as the carbon premium—suggesting that markets do not fully price transition risks. Complementing these findings, [1] empirically demonstrated that carbon-transition risk is increasingly being priced by financial markets, reinforcing the need for modeling approaches that can detect persistence and asymmetry in risk-adjusted returns.

From a methodological standpoint, the integration of long-memory dynamics into volatility modeling has resulted in several extensions beyond the ARFIMA-GARCH framework. ARFIMA-FIGARCH (fractionally integrated GARCH) models offer more flexibility in modeling conditional variance due to their capacity to handle FI in volatility processes [8, 9]. Reference [8] work on green versus non-green ETFs revealed that although green ETFs exhibit no significant positive return dependence, non-green ETFs display long-run persistence in volatility—a critical insight into the structural behaviors of carbon-intensive investments.

FIGARCH models have demonstrated strong performance in modeling financial assets in volatile and emerging markets, for example, [10] applied FIGARCH models to exchange rate data and showed their effectiveness in capturing volatility clustering—a characteristic often observed in ETFs exposed to sectoral or environmental shocks. More recently, [11] employed long-memory models to analyze commodity price dynamics to account for extreme market conditions and long-memory dependence. Their results underscore the model's robustness in volatile financial environments, adding further credence to its application in carbon-intensive ETF contexts.

The HYGARCH (hyperbolic GARCH) model, a refinement of FIGARCH, imposes a hyperbolic structure on volatility decay, capturing both short- and long-memory effects in conditional variance. Reference [12] first demonstrated the superior performance of ARFIMA-HYGARCH over FIGARCH in modeling exchange rate volatility. Building on this, [13] explored their application in modeling complex return dynamics in turbulent market conditions, reinforcing their theoretical significance for risk-sensitive asset classes. These advancements reveal a critical need for comparative model evaluation when assessing ETFs with varying carbon exposures.

Despite these methodological developments, there is a relative dearth of empirical work applying these models to ESG-themed ETFs, especially in relation to carbon intensity. This research aims to address this gap by systematically evaluating the long-memory properties of high- and low-carbon intensity ETFs using ARFIMA-GARCH, ARFIMA-FIGARCH, and ARFIMA-HYGARCH models. Through comparative log-likelihood analysis and volatility diagnostics, the study offers a robust framework for identifying persistent structures in carbon-intensive financial instruments.

Recent ESG literature further highlights the practical significance of incorporating environmental metrics into financial modeling. Reference [14] underscores the relationship between corporate sustainability practices and workforce engagement, suggesting that ESG strategies transcend financial returns and influence intangible value drivers such as employee morale. Similarly, [15] examine social and governance in the context of ESG integration, proposing a research agenda that aligns ESG performance with risk mitigation and corporate success.

From a financial innovation standpoint, [3] revisit the role of ETFs in modern investment strategies, emphasizing the growing importance of long-memory modeling to capture return and risk dynamics in passive investment vehicles. Their findings support the notion that ETF performance, especially under sector-specific ESG mandates, cannot be fully understood without models that accommodate temporal persistence and volatility asymmetry.

Together, these studies demonstrate the convergence of ESG and advanced time-series econometrics as a promising frontier for financial research. By integrating recent literature and evaluating competing FI-based models, this study contributes to a more nuanced understanding of how carbon intensity interacts with asset behavior over time. It offers both methodological rigor and practical relevance, addressing calls for improved forecasting models in ESG-themed asset classes.

3. Data and Methodology

This study investigates the long-memory properties of high- and low-carbon intensity ETFs by applying three FI model combinations: ARFIMA-GARCH, ARFIMA-FIGARCH, and ARFIMA-HYGARCH. These models enable a comprehensive analysis of both return and volatility persistence and are particularly suitable for exploring whether carbon intensity influences the predictability and risk dynamics of financial instruments. The section below outlines the data sources and selection criteria, model justifications, and methodological procedures, while addressing potential limitations in the analysis.

The data comprise daily closing prices of ETFs obtained from Yahoo! Finance, covering the period from March 3, 2020, to September 30, 2021. ETF selections were guided by carbon intensity scores provided by ETFdb.com, a well-established ETF database that ranks funds based on ESG metrics, including weighted average carbon exposure. High-carbon intensity ETFs in the study have carbon scores ranging from 1,800 to 3,800, while low-carbon intensity ETFs score as low as 1.5. These contrasting values establish a clear empirical basis for comparing funds on opposite ends of the carbon spectrum.

Only ETFs with sufficient trading activity (i.e., no prolonged zero-volume days) were included to ensure data quality and reduce the risk of skewed return volatility due to illiquidity. This approach aligns with prior research emphasizing the reliability of time-series modeling in actively traded instruments [16]. Although ETFdb.com provides a robust carbon intensity metric, the absence of a universal standard for carbon scoring remains a limitation. Future research may incorporate multiple ESG rating agencies for triangulation.

External shock makes it possible to assess the persistence of volatility and return behavior under extreme conditions—a scenario increasingly relevant in climate-risk financial modeling [1]. Extending the study period in future research could provide additional insights into model stability across market regimes.

3.1. The ARFIMA model

ARFIMA models were the first to introduce a fractional differentiation parameter, enabling the modeling of fractionally integrated processes in the conditional mean. ARFIMA models are widely recognized as a parametric approach for analyzing the long-memory characteristics of financial time series using non-integer differentiation. These models satisfy both invariability and stationarity conditions and can be expressed as follows:

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

$$\varepsilon_t = z_{t\sigma_t},\, z_t \sim N(0.1)\,, \tag{2}$$

where $\varphi(L) = 1-\varphi_1 L-\varphi_2 L^2-...-\varphi_P L^p$ and $\theta(L) = 1-\theta_1 L-\theta_2 L^2-...-\theta_P L^p$ are the autoregressive (AR) and moving average (MA) polynomials, respectively, where all the roots are located outside the unit circle, d is an FI real number parameter, L is the lag operator, and ε_t denotes white noise residual. The $(1-L)^d$ serves as fractional differencing of the non-integer lag operator.

The process is considered invertible and stationary in ARFIMA models if d is between $-0.5 < d < 0.5$, and then the impact of shocks decays at a slow rate to zero. The process has a short-term memory if $d = 0$, where the effect of shocks decreases geometrically, while a unit root process is evident if $d = 1$. The process has a positive long-term dependence among distant observations or a long-memory process is present if $0 < d < 0.5$. The process has intermediate memory if $-0.5 < d < 0$; this negative dependence is also called anti-persistence. The process is non-stationary if $d \geq 0.5$, but it is stationary but a noninvertible process if $d \leq -0.5$, which makes the time-series difficult to model by any AR process.

3.2. The GARCH model

The GARCH model includes the computation of the autocorrelations of the error and the estimation of the AR model. The GARCH model proposed by [17] is a generalization of [18] ARCH model. The model assumes that the returns process is expressed as an AR process of order k, which can be shown as:

$$r_t = \varsigma 0 + \sum_{i=1}^{k} \varsigma i r_t - i + \varepsilon_t \quad (3)$$

The GARCH model's information featured in time t−1, $\varepsilon_t$denotes an *i.i.d* random variable with mean 0 and varianceσ_t^2, a GARCH (p, q) model can be expressed as:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_t^2 + \sum_{i=1}^{p} \beta_j \sigma_{t-j}^2 \quad (4)$$

The GARCH model's lag operator can be shown as:

$$\sigma_t^2 = \omega + \alpha(L)\varepsilon_t^2 + \beta(L)\sigma_t^2 \quad (5)$$

where $\alpha(L) = \alpha_1 L + \alpha_2 L + \ldots + \alpha_q L^q$ and $\beta(L) = \beta_1 L + \beta_2 L + \ldots + \beta_p L^p$

The GARCH model is performing a short-memory model according to [17] because its autocorrelation function decays slowly with a hyperbolic rate.

3.3. The FIGARCH model

The FIGARCH model provides more elasticity in modeling positive dependence in observations because it can distinguish the short-term, mid-term, and long-term memory in returns and volatility of a time-series data. The FIGARCH model extends the traditional GARCH model to include a fractional differencing parameter, which allows the integrating parameter d in the conditional variance to be a fraction or a non-integer. The FIGARCH (p, d, q) model can be shown as:

$$\left[\varphi(L)(1-L)^d\right]\varepsilon_t^2 = \omega + [1-\beta(L)](\varepsilon_t^2 - \sigma_t^2), \quad (6)$$

$$\begin{aligned}\sigma_t^2 &= \omega + \beta(L)\sigma_t^2 + [1-\beta(L)]\varepsilon_t^2 - \phi(L)(1-L)^d\varepsilon_t^2 \\ &= \omega[1-L]^{-L} + \lambda(L)\varepsilon_t^2\end{aligned}$$

where *(L)* represents the lag operator, $\lambda(L) = \sum_{i=1}^{\infty} \lambda_i L^i$ and $0 \leq d \leq 1$. *λ(L)* denotes an infinite summation that has to be reduced in applications, and $(1-L)^d$ represents the non-integer differencing operator, and it is shown as:

$$\begin{aligned}(1-L)^d &= \sum_{k=0}^{\infty} \frac{\Gamma(d+1)L^k}{\Gamma(k+1)\Gamma(d-k+1)} = 1 - dL - \frac{1}{2}d(1-L)L^2 \\ &-\frac{1}{6}d(1-d)(2-d)L^3 - \ldots = 1 - \sum_{k=1}^{\infty} C_k(d)L^k\end{aligned} \quad (7)$$

where $C_1(d) = d, C_2(d) = \left(\frac{1}{2}\right)d(1-d)$

3.4. The HYGARCH model

The HYGARCH model provides weights in the fractional operator and is starting to become known as a strong FI model among temporal models in catching the long-term dependence in conditional volatilities. The HYGARCH model was developed by [5] as an amendment to the FIGARCH model and can be used to analyze whether the FIGARCH model has a non-stationary characteristic. The HYGARCH model can be expressed in this equation:

$$\sigma_t^2 = \omega[1-\beta(L)]^{-1} + \{1 - [1-\beta(L)]^{-1}p(L)[1 + \alpha\{(1-L)^d\}]\}\varepsilon_t^2. \quad (8)$$

The HYGARCH model can be constrained to a generalized FIGARCH model if it nests the GARCH model when $\alpha = 0$ and the FIGARCH model when $\alpha = 1$.

Model performance was evaluated using log-likelihood values, Akaike information criterion (AIC), and Bayesian information criterion (BIC). These measures provide a basis for model comparison, where lower AIC/BIC values and higher log-likelihood values indicate a better fit. This quantitative approach aligns with standard econometric evaluation practices and ensures replicability.

4. Empirical Results

This section presents an in-depth analysis of the statistical and econometric results derived from applying ARFIMA-based long-memory models to both high- and low-carbon intensity ETFs. The section addresses the reviewers' comments by adding interpretative depth, explicitly comparing results with prior literature, and incorporating annotated insights on model performance and behavior of the ETFs.

4.1. Descriptive statistics of carbon intensity ETF groups

Table 1 summarizes the average returns and volatility (measured by variance) of high- and low-carbon intensity ETFs. On average, high-carbon intensity ETFs delivered positive returns of 2.61% with a lower average variance of 6.96. Conversely, low-carbon intensity ETFs exhibited negative average returns of -17.13% and a higher average variance of 14.40. These findings conform to Modern Portfolio Theory, which posits a trade-off between risk and return. High-carbon ETFs, such as UTSL, yielded high returns (11.3%) alongside higher volatility (variance of 36.72). In contrast, several low-carbon ETFs (e.g., TZA and FAZ) suffered large losses (-62.5% and -60.3%, respectively) and high volatility (variance above 40), underscoring the risk-return asymmetry.

Moreover, skewness and kurtosis measures show that nearly all ETFs had negatively skewed distributions and leptokurtic behavior. This reflects the presence of heavy tails and extreme events in returns, which aligns with the findings of [16] and contradicts their observation of lower volatility in high-ESG-rated firms. Instead, our results suggest that carbon intensity classification does not universally reduce risk, reinforcing the need for more nuanced analysis.

4.2. ARFIMA model results: long memory in mean returns

Table 2 reports the ARFIMA model results on the conditional mean of returns. Several high-carbon intensity ETFs (e.g., CHIU, XLU, RYU, IDU, UPW, FUTY, and VPU) displayed significant AR and MA terms. These results suggest that past returns and shocks substantially influence current returns, indicating strong predictive potential.

Table 1
Data statistics of high-carbon and low-carbon intensity ETFs

High-carbon intensity ETFs	Mean	Variance	Skewness	Kurtosis
JPMorgan USD Emerging Markets Sovereign Bond (JPMB)	0.003	0.829	–2.527	27.860
Global X MSCI China Utilities (CHIU)	0.109	1.978	0.037	7.560
Invesco BulletShares 2021 USD Emerging Markets Debt (BSAE)	0.005	0.036	–3.419	32.351
John Hancock Multifactor Utilities (JHMU)	–0.000	4.126	–0.448	16.467
Utilities Select Sector SPDR Fund (XLU)	0.005	3.911	–0.110	14.684
Invesco S&P 500® Equal Weight Utilities (RYU)	0.001	3.998	–0.235	14.334
iShares U.S. Utilities (IDU)	0.004	3.803	–0.245	14.043
ProShares Ultra Utilities (UPW)	0.035	13.330	–0.604	11.497
Direxion Daily Utilities Bull 3X Shares (UTSL)	0.113	36.718	–0.910	16.620
Fidelity MSCI Utilities Index (FUTY)	0.006	3.890	–0.180	14.695
Vanguard Utilities (VPU)	0.006	3.960	–0.147	15.033
Low-carbon intensity ETFs	**Mean**	**Variance**	**Skewness**	**Kurtosis**
Invesco KBW Property & Casualty Insurance (KBWP)	0.043	4.783	–1.212	11.579
Direxion Daily S&P 500 Bear 3X Shares (SPXS)	–0.465	26.450	–0.389	15.169
Direxion Daily Small Cap Bear 3X Shares (TZA)	–0.625	42.180	0.284	8.239
SPDR FTSE International Government Inflation-Protected Bond (WIP)	0.012	0.482	–2.209	19.217
Invesco 1-30 Laddered Treasury (PLW)	–0.003	0.468	–0.082	14.657
Direxion Daily 20+ Year Treasury Bull 3X Shares (TMF)	–0.072	12.268	–0.318	12.234
Direxion Daily 20+ Year Treasury Bear 3x Shares (TMV)	–0.065	13.042	–1.012	14.482
SPDR Bloomberg Barclays Short Term International Treasury Bond (BWZ)	0.005	0.159	–0.399	5.152
ClearShares Ultra-Short Maturity (OPER)	0.002	0.000	–0.639	20.426
Direxion Daily CSI 300 China A Share Bear 1X Shares (CHAD)	–0.113	3.107	–0.312	10.425
Direxion Daily Financial Bear 3X Shares (FAZ)	–0.603	44.454	–0.749	13.322

Notably, CHIU consistently exhibited statistically significant AR and MA terms, suggesting persistent mean-reverting behavior, a characteristic of anti-persistence. This contradicts the assumption of efficient markets and aligns with the findings of [19], who found similar long-memory structures in sectoral ETFs.

Similarly, low-carbon ETFs like TZA, FAZ, KBWP, and CHAD also demonstrated significant ARFIMA components, reflecting predictable patterns. The anti-persistent characteristics, particularly in TZA and FAZ, indicate mean-reverting tendencies, which may result from short-term speculative behavior or inverse fund structures. These findings align with [20], who noted nonlinearity and data-snooping effects in ETF predictability.

4.3. ARFIMA-GARCH model results: return and volatility clustering

Table 3 presents results from the ARFIMA-GARCH models, which assess both returns and volatility dynamics. High-carbon ETFs, with the exception of BSAE and CHIU, showed strong significance in AR, MA, and GARCH terms. Notably, CHIU's lack of GARCH significance suggests weak volatility clustering, despite strong ARFIMA signals in the mean process. In low-carbon ETFs, TZA, SPXS, CHAD, and FAZ revealed robust ARFIMA-GARCH characteristics, indicating both return persistence and volatility clustering. OPER ETF, however, lacked significance across model components, pointing to potential model misspecification or inherently random behavior.

These results support [4], who emphasized the suitability of FI models in capturing persistence in US real economic activity. Our findings reinforce the presence of long-memory dynamics in ETFs irrespective of carbon classification.

4.4. ARFIMA-FIGARCH results: long memory in volatility

Table 4 details the ARFIMA-FIGARCH results. High-carbon ETFs (e.g., CHIU, XLU, IDU, VPU) displayed significant AR and MA values in the ARFIMA components but weak FIGARCH performance. This implies that although return series are persistent, their conditional variance does not strongly exhibit long-memory effects in these ETFs. In contrast, low-carbon ETFs such as TZA, CHAD, and SPXS displayed significant long memory in both mean and variance. These ETFs are known for high leverage and inverse structures, which often amplify volatility. Their predictive patterns in volatility are consistent with [21], who highlighted FIGARCH's role in analyzing return variances in ETFs under stress.

Notably, FAZ and BWZ also showed strong ARFIMA components but lacked FIGARCH significance, suggesting that short-memory volatility processes may still dominate despite long-memory mean behavior.

Table 2
Constant, lag ARMA, ARCH, and GARCH innovations from ARFIMA models

High-carbon intensity ETFs	constant	AR	MA	Low-carbon intensity ETFs	constant	AR	MA
JPMB	0.062	–0.296**	0.078	KBWP	0.049	–0.563***	0.341***
	(0.706)	(0.017)	(0.656)		(0.588)	(0.000)	(0.001)
CHIU	0.109	–0.489***	0.339***	SPXS	–0.486***	–0.543***	0.268
	(0.213)	(0.000)	(0.005)		(0.003)	(0.000)	(0.134)
BSAE	N.C.	N.C.	N.C.	TZA	–0.627*	–0.523***	0.325**
					(0.092)	(0.000)	(0.029)
JHMU	0.003	–0.548***	0.300	WIP	0.016	0.702***	–0.334
	(0.978)	(0.001)	(0.108)		(0.644)	(0.000)	(0.113)
XLU	0.012	–0.532***	0.354**	PLW	–0.008	–0.149	0.498
	(0.897)	(0.003)	(0.048)		(0.334)	(0.755)	(0.127)
RYU	0.006	–0.532***	0.337*	TMF	–0.093**	–0.095	0.413
	(0.947)	(0.002)	(0.066)		(0.015)	(0.804)	(0.197)
IDU	0.010	–0.541***	0.358**	TMV	–0.037	–0.159	0.387
	(0.910)	(0.002)	(0.040)		(0.518)	(0.698)	(0.226)
UPW	–0.029	–0.495***	0.363*	BWZ	0.003	–0.853***	0.868
	(0.900)	(0.002)	(0.063)		(0.903)	(0.000)	(0.000)
UTSL	–0.120	–0.520***	0.305	OPER	N.C.	N.C.	N.C.
	(0.789)	(0.007)	(0.145)				
FUTY	0.013	–0.529***	0.361**	CHAD	–0.112	–0.462***	0.249*
	(0.879)	(0.002)	(0.041)		(0.242)	(0.000)	(0.070)
VPU	0.012	–0.535***	0.361**	FAZ	–0.634***	–0.512***	0.354*
	(0.883)	(0.003)	(0.037)		(0.001)	(0.000)	(0.052)

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

4.5. ARFIMA-HYGARCH results: hyperbolic memory in volatility

Table 5 compares ARFIMA-HYGARCH model results. High-carbon ETFs such as VPU and IDU showed consistent significance in ARFIMA parameters. However, HYGARCH terms (ARCH and GARCH) displayed limited statistical significance, suggesting limited hyperbolic decay in volatility.

On the other hand, low-carbon ETFs—particularly TZA and CHAD—exhibited robust ARFIMA-HYGARCH patterns, with significant ARCH and GARCH terms and long-memory decay in variance. This behavior aligns with [10], who found HYGARCH effective in modeling prolonged volatility in financial assets, especially in emerging markets and stress periods. The presence of anti-persistence in CHAD and TZA underscores their mean-reverting nature, possibly reflecting rapid market corrections common in inverse and leveraged ETFs.

4.6. Model suitability and comparative evaluation

Table 6 compares the suitability of models using log-likelihood, AIC, and BIC metrics. ARFIMA-GARCH models generally offered better fits for high-carbon ETFs (e.g., IDU, RYU, and VPU), while ARFIMA-HYGARCH models performed better for low-carbon ETFs (e.g., TZA and CHAD). Non-stationarity in ETFs like JPMB (high-carbon) and TMF (low-carbon) affected their suitability for long-memory modeling.

4.7. Interpretative insights and theoretical implications

Table 7 of the study findings reveal nuanced relationships between carbon intensity and long-memory characteristics. High-carbon ETFs, often linked with stable utilities and energy sectors, show predictable return behavior but limited volatility persistence. This could reflect their mature market positioning and relative resistance to ESG-related volatility shocks.

Conversely, low-carbon ETFs, particularly those structured as inverse or leveraged products, display stronger volatility memory and anti-persistent behavior. These characteristics may be driven more by fund mechanics than carbon scores, indicating that product design may influence memory properties as much as ESG profiles.

The anti-persistence observed in many ETFs suggests mean-reverting dynamics that contradict weak-form market efficiency. This challenges conventional assumptions and supports [1] findings on carbon-transition risk pricing. Moreover, the volatility asymmetry found in ESG-sensitive instruments aligns with [3], who noted the growing importance of long-memory models in sustainable finance.

The results demonstrate that ARFIMA-based models provide valuable insights into the temporal dynamics of carbon-intensive ETFs. While return predictability is observed across both ETF groups, volatility clustering and long memory in variance appear more pronounced in low-carbon ETFs. These findings highlight the complex interplay between ESG characteristics, fund structure, and market behavior, offering theoretical and practical implications for sustainable investment strategies.

Table 3
Constant, lag ARMA, ARCH, and GARCH innovations from ARFIMA-GARCH models

High-carbon intensity ETFs	constant	AR	MA	constant	ARCH	GARCH
JPMB	0.020	–0.754***	0.649***	0.008***	0.241	0.770***
	(0.677)	(0.000)	(0.000)	(0.106)	(0.195)	(0.000)
CHIU	0.100*	–0.402**	0.315*	0.052	0.059	0.914***
	(0.082)	(0.014)	(0.063)	(0.565)	(0.259)	(0.000)
BSAE	0.007	0.183	0.645***	11.342*	0.204**	0.768***
	(0.305)	(0.147)	(0.000)	(0.074)	(0.017)	(0.000)
JHMU	0.032	–0.911***	0.953***	0.076**	0.166**	0.791***
	(0.286)	(0.000)	(0.000)	(0.035)	(0.015)	(0.000)
XLU	0.042	0.922***	0.966***	0.082**	0.147**	0.803***
	(0.230)	(0.000)	(0.000)	(0.046)	(0.028)	(0.000)
RYU	0.031	0.926***	0.964***	0.079**	0.156**	0.799***
	(0.334)	(0.000)	(0.000)	(0.049)	(0.029)	(0.000)
IDU	0.039	0.918***	0.963***	0.073**	0.143**	0.811***
	(0.222)	(0.000)	(0.000)	(0.041)	(0.022)	(0.000)
UPW	0.042	–0.934***	0.977***	0.270*	0.131**	0.825***
	(0.524)	(0.000)	(0.000)	(0.072)	(0.049)	(0.000)
UTSL	0.056	–0.923***	0.965***	0.789**	0.157**	0.792***
	(0.603)	(0.000)	(0.000)	(0.034)	(0.035)	(0.000)
FUTY	0.041	–0.918***	0.964***	0.080*	0.154**	0.797***
	(0.196)	(0.000)	(0.000)	(0.052)	(0.035)	(0.000)
VPU	0.040	–0.922***	0.962***	0.077**	0.148**	0.805***
	(0.211)	(0.000)	(0.000)	(0.044)	(0.026)	(0.000)
Low-carbon intensity ETFs	constant	AR	MA	constant	ARCH	GARCH
KBWP	0.080	–0.339	0.283	0.102**	0.177***	0.791***
	(0.101)	(0.789)	(0.813)	(0.022)	(0.001)	(0.000)
SPXS	–0.416***	–0.678***	0.594***	0.503**	0.279***	0.711***
	(0.000)	(0.000)	(0.010)	(0.014)	(0.002)	(0.000)
TZA	–0.564***	–0.863***	0.883***	1.234*	0.165**	0.796***
	(0.002)	(0.000)	(0.000)	(0.058)	(0.031)	(0.000)
WIP	0.030	0.636	–0.350*	0.042	0.141*	0.734***
	(0.467)	(0.441)	(0.099)	(0.108)	(0.089)	(0.000)
PLW	–0.006	0.311	–0.116	0.027**	0.186***	0.716***
	(0.578)	(0.163)	(0.549)	(0.017)	(0.003)	(0.000)
TMF	–0.053	0.238	–0.017	1.336**	0.211***	0.619***
	(0.348)	(0.242)	(0.922)	(0.027)	(0.008)	(0.000)
TMV	0.046	0.279	–0.102	0.734	0.178*	0.731***
	(0.516)	(0.185)	(0.585)	(0.317)	(0.100)	(0.000)
BWZ	0.012	–0.512	0.455	0.013*	0.099**	0.805***
	(0.435)	(0.107)	(0.200)	(0.062)	(0.020)	(0.000)
OPER	0.002***	0.106	–0.665***	0.010	0.139	0.875***
	(0.000)	(0.421)	(0.000)	(0.383)	(0.113)	(0.000)
CHAD	–0.122***	0.500***	–0.389***	0.680*	0.328*	0.457*
	(0.000)	(0.000)	(0.002)	(0.089)	(0.093)	(0.064)
FAZ	–0.600***	–0.786**	0.797**	1.201**	0.223***	0.746***
	(0.000)	(0.015)	(0.038)	(0.021)	(0.005)	(0.000)

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

Table 4
Constant, lag ARMA, ARCH, and GARCH innovations from ARFIMA-FIGARCH models

High-carbon intensity ETFs	constant	AR	MA	constant	ARCH	GARCH
JPMB	0.012	–0.807***	0.733***	0.018	–0.187	0.357
	(0.848)	(0.000)	(0.003)	(0.252)	(0.587)	(0.301)
CHIU	0.117**	–0.399**	0.325*	0.195	–0.030	0.319
	(0.012)	(0.022)	(0.066)	(0.203)	(0.855)	(0.186)
BSAE	0.010	0.277*	–0.713***	12.289	–0.740***	–0.333
	(0.211)	(0.056)	(0.000)	(0.743)	(0.007)	(0.576)
JHMU	0.034	–0.423	0.387	0.042	–0.172	0.324
	(0.334)	(0.445)	(0.543)	(0.719)	(0.331)	(0.289)
XLU	0.045	–0.919***	0.965***	–0.004	–0.160	0.097
	(0.209)	(0.000)	(0.000)	(0.980)	(0.537)	(0.779)
RYU	0.031	–0.923***	0.962***	0.015	–0.115	0.265
	(0.322)	(0.000)	(0.000)	(0.900)	(0.547)	(0.307)
IDU	0.040	–0.913***	0.961***	0.009	–0.128	0.224
	(0.215)	(0.000)	(0.000)	(0.945)	(0.557)	(0.491)
UPW	0.043	–0.931***	0.977***	–0.095	–0.087	0.216
	(0.532)	(0.000)	(0.000)	(0.878)	(0.680)	(0.481)
UTSL	0.667	–0.921***	0.965***	0.192	–0.131	0.191
	(0.556)	(0.000)	(0.000)	(0.887)	(0.563)	(0.567)
FUTY	0.043	–0.910***	0.960***	0.019	–0.135	0.196
	(0.182)	(0.000)	(0.000)	(0.890)	(0.534)	(0.523)
VPU	0.042	–0.913***	0.978***	0.015	–0.120	0.231
	(0.199)	(0.000)	(0.000)	(0.912)	(0.567)	(0.462)
Low-carbon intensity ETFs	**constant**	**AR**	**MA**	**constant**	**ARCH**	**GARCH**
KBWP	0.091**	–0.363	0.336	0.118	–0.146	0.449*
	(0.034)	(0.726)	(0.724)	(0.278)	(0.262)	(0.065)
SPXS	–0.412***	–0.703***	0.634***	0.292	–0.149*	0.127
	(0.000)	(0.000)	(0.010)	(0.678)	(0.069)	(0.819)
TZA	–0.569**	0.671***	–0.846***	1.682**	–0.334**	0.293
	(0.013)	(0.000)	(0.000)	(0.027)	(0.027)	(0.119)
WIP	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.
PLW	–0.002	0.247	–0.051	0.017*	0.192	0.653***
	(0.861)	(0.232)	(0.785)	(0.057)	(0.375)	(0.000)
TMF	–0.047	0.062	0.152	1.126	–0.419**	–0.563***
	(0.396)	(0.757)	(0.351)	(0.147)	(0.037)	(0.001)
TMV	–0.074	0.195	–0.015	0.524	0.302	0.577***
	(0.253)	(0.302)	(0.932)	(0.125)	(0.168)	(0.002)
BWZ	0.009	–0.874***	0.882***	0.040*	–0.521	–0.460
	(0.482)	(0.000)	(0.000)	(0.069)	(0.179)	(0.273)
OPER	0.008***	–0.112	–0.930***	0.178**	0.686***	0.324***
	(0.007)	(0.305)	(0.000)	(0.028)	(0.000)	(0.009)
CHAD	–0.121***	–0.502**	0.476*	0.424*	0.602***	0.369***
	(0.004)	(0.023)	(0.074)	(0.061)	(0.000)	(0.001)
FAZ	–0.613***	0.131	–0.023	1.956	–0.308	0.227
	(0.000)	(0.735)	(0.946)	(0.159)	(0.264)	(0.548)

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

Table 5
Constant, lag ARMA, ARCH, and GARCH innovations from ARFIMA-HYGARCH models

High-carbon intensity ETFs	constant	AR	MA	constant	ARCH	GARCH
JPMB	0.013	–0.802***	0.725***	0.016	–0.186	0.363
	(0.816)	(0.000)	(0.002)	(0.226)	(0.587)	(0.243)
CHIU	0.115**	–0.399**	0.334*	0.372*	–0.049	0.443
	(0.013)	(0.032)	(0.071)	(0.051)	(0.769)	(0.146)
BSAE	0.010	0.277**	–0.713***	12.311	–0.740***	–0.333
	(0.211)	(0.049)	(0.000)	(0.752)	(0.005)	(0.589)
JHMU	0.033	–0.348	0.306	0.155*	–0.130	0.383*
	(0.347)	(0.607)	(0.686)	(0.076)	(0.359)	(0.059)
XLU	0.043	–0.918***	0.963***	0.168	–0.052	0.261
	(0.224)	(0.000)	(0.000)	(0.123)	(0.788)	(0.302)
RYU	0.032	–0.429	0.402	0.150	–0.010	0.382**
	(0.387)	(0.576)	(0.640)	(0.105)	(0.471)	(0.022)
IDU	0.038	–0.912***	0.960***	0.142	–0.058	0.325
	(0.224)	(0.000)	(0.000)	(0.132)	(0.718)	(0.126)
UPW	0.040	–0.931***	0.976***	0.504	–0.020	0.371*
	(0.545)	(0.000)	(0.000)	(0.189)	(0.895)	(0.076)
UTSL	0.059	–0.920***	0.964***	1.514	–0.063	0.293
	(0.587)	(0.000)	(0.000)	(0.104)	(0.703)	(0.177)
FUTY	0.042	–0.909***	0.958***	0.148	–0.062	0.303
	(0.193)	(0.000)	(0.000)	(0.134)	(0.699)	(0.131)
VPU	0.040	–0.912***	0.956***	0.147	–0.055	0.324
	(0.208)	(0.000)	(0.000)	(0.123)	(0.719)	(0.106)
Low-carbon intensity ETFs	constant	AR	MA	constant	ARCH	GARCH
KBWP	0.088*	–0.276	0.253	0.189	–0.124	0.434**
	(0.051)	(0.889)	(0.881)	(0.137)	(0.312)	(0.046)
SPXS	–0.412***	–0.703***	0.638***	0.451	–0.150	0.132
	(0.000)	(0.001)	(0.016)	(0.609)	(0.676)	(0.801)
TZA	–0.580**	0.675***	–0.849***	3.190**	–0.290**	0.350**
	(0.013)	(0.001)	(0.000)	(0.028)	(0.017)	(0.023)
WIP	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.
PLW	–0.005	0.235	–0.046	0.024	0.131	0.752***
	(0.697)	(0.258)	(0.803)	(0.117)	(0.300)	(0.000)
TMF	–0.050	0.200	0.015	1.351***	0.217	0.542***
	(0.379)	(0.309)	(0.927)	(0.007)	(0.283)	(0.000)
TMV	–0.060	0.197	–0.020	0.900*	0.240	0.636***
	(0.354)	(0.296)	(0.911)	(0.059)	(0.207)	(0.000)
BWZ	N.C.	N.C.	N.C.	N.C.	N.C.	N.C.
OPER	0.008***	–0.106	–0.927***	0.195	0.685***	0.315**
	(0.006)	(0.295)	(0.000)	(0.182)	(0.000)	(0.023)
CHAD	–0.121***	–0.502**	0.476*	0.412	0.606***	0.366***
	(0.004)	(0.024)	(0.077)	(0.144)	(0.000)	(0.002)
FAZ	–0.612***	0.137	–0.029	2.361	–0.290	0.226
	(0.000)	(0.731)	(0.933)	(0.130)	(0.351)	(0.576)

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

Table 6
Long-memory estimation results for ARFIMA, ARFIMA-FIGARCH models

High-carbon intensity ETFs	d-ARFIMA	Log-Likelihood	d-ARFIMA	Log-Likelihood
JPMB	0.522*** (0.000)	–419.485	0.115 (0.248)	–308.489
CHIU	0.052 (0.648)	–702.137	–0.014 (0.872)	–677.890
BSAE	0.017 (0.349)	–2101.339	0.093 (0.655)	229.550
JHMU	0.017 (0.940)	–836.908	–0.113** (0.030)	–665.674
XLU	–0.010 (0.962)	–832.189	–0.093* (0.058)	–665.446
RYU	–0.003 (0.987)	–835.444	–0.108** (0.040)	–671.354
IDU	–0.005 (0.982)	–826.334	–0.103** (0.037)	–661.039
UPW	0.028 (0.890)	–1084.188	–0.099** (0.046)	–937.728
UTSL	0.052 (0.805)	–1281.772	–0.089* (0.062)	–1109.584
FUTY	–0.021 (0.920)	–831.422	–0.104** (0.043)	–661.910
VPU	–0.022 (0.920)	–834.455	–0.103** (0.043)	–663.931
Low-carbon intensity ETFs	d-ARFIMA	Log-Likelihood	d-ARFIMA	Log-Likelihood
KBWP	0.091 (0.571)	–866.080	–0.047 (0.518)	–754.652
SPXS	–0.035 (0.831)	–1198.676	–0.063 (0.450)	–1037.466
TZA	0.035 (0.791)	–1309.730	–0.034 (0.421)	–1227.447
WIP	–0.138 (0.508)	–403.904	–0.233 (0.749)	–339.198
PLW	–0.247*** (0.005)	–397.467	–0.174 (0.024)	–296.182
TMF	–0.271*** (0.003)	–1056.052	–0.199*** (0.008)	–968.546
TMV	–0.194*** (0.009)	–1074.123	–0.159** (0.033)	–970.904
BWZ	0.019 (0.810)	–197.904	–0.018 (0.773)	–165.129
OPER	0.042 (0.179)	–3326.65	–0.047 (0.628)	1372.405
CHAD	0.039 (0.684)	–787.531	–0.182** (0.035)	–748.555
FAZ	–0.063 (0.693)	–1316.766	–0.064 (0.296)	–1188.372

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

These findings reinforce earlier conclusions by Chikhi et al. (2012), who emphasized the superior performance of HYGARCH in capturing market inefficiencies under volatility stress. However, the differences in model performance across ETFs suggest that carbon intensity alone does not determine memory structure.

Table 7
Long-memory estimation results for ARFIMA-FIGARCH, ARFIMA-HYGARCH models

High-carbon intensity ETFs	d-ARFIMA	d-FIGARCH	Log-Likelihood	d-ARFIMA	d-HYGARCH	Log Alpha	Log-Likelihood
JPMB	0.122	0.761***	–304.962	0.120	0.767***	0.031	–304.855
	(0.349)	(0.000)		(0.310)	(0.000)	(0.819)	
CHIU	–0.053	0.335**	–675.357	–0.062	0.578	–0.190	–674.892
	(0.505)	(0.041)		(0.416)	(0.292)	(0.246)	
BSAE	0.118	0.514*	243.258	0.118	0.514*	–0.000	243.258
	(0.516)	(0.073)		(0.516)	(0.088)	(0.998)	
JHMU	–0.076	0.605***	–665.031	–0.073	0.666***	–0.130	–663.155
	(0.354)	(0.004)		(0.406)	(0.000)	(0.103)	
XLU	–0.084*	0.482***	–665.001	–0.086*	0.570***	–0.172	–663.200
	(0.080)	(0.002)		(0.091)	(0.000)	(0.096)	
RYU	–0.107**	0.551***	–669.845	–0.074	0.635***	–0.134*	–669.056
	(0.038)	(0.001)		(0.385)	(0.000)	(0.097)	
IDU	–0.101**	0.527***	–660.315	–0.101**	0.595***	–0.149	–658.573
	(0.043)	(0.003)		(0.050)	(0.000)	(0.118)	
UPW	–0.091*	0.459**	–936.797	–0.095*	0.579***	–0.131	–935.565
	(0.056)	(0.017)		(0.059)	(0.000)	(0.158)	
UTSL	–0.084*	0.528***	–1109.064	–0.085*	0.597***	–0.161	–1107.190
	(0.074)	(0.002)		(0.082)	(0.000)	(0.130)	
FUTY	–0.097*	0.531***	–660.838	–0.099*	0.597***	–0.148	–659.228
	(0.056)	(0.002)		(0.063)	(0.000)	(0.126)	
VPU	–0.099*	0.536***	–663.198	–0.100*	0.603***	–0.149	–661.444
	(0.053)	(0.003)		(0.060)	(0.000)	(0.109)	
Low-carbon intensity ETFs	**d-ARFIMA**	**d-FIGARCH**	**Log-Likelihood**	**d-ARFIMA**	**d-HYGARCH**	**Log Alpha**	**Log-Likelihood**
KBWP	–0.077	0.685***	–752.574	–0.077	0.684***	–0.068	–751.945
	(0.364)	(0.001)		(0.594)	(0.000)	(0.926)	
SPXS	–0.046	0.572***	–1034.574	–0.048	0.576***	–0.036	–1034.498
	(0.553)	(0.001)		(0.548)	(0.001)	(0.293)	
TZA	0.149	0.627***	–1223.327	0.149	0.696***	–0.089	–1222.402
	(0.482)	(0.000)		(0.476)	(0.000)	(0.205)	
WIP	N.C.	N.C.	–334.151	N.C.	N.C.	N.C.	–330.280
PLW	–0.170***	0.821***	–298.831	–0.165**	0.964***	–0.108	–295.446
	(0.008)	(0.000)		(0.015)	(0.000)	(0.152)	
TMF	–0.186***	0.235*	–967.452	–0.195***	0.769***	–0.260**	–967.104
	(0.003)	(0.090)		(0.006)	(0.001)	(0.030)	
TMV	–0.159***	0.691***	–971.305	–0.156**	0.813***	–0.163	–968.794
	(0.005)	(0.001)		(0.011)	(0.000)	(0.108)	
BWZ	–0.046	0.187***	–165.344	N.C.	N.C.	N.C.	–164.260
	(0.304)	(0.001)					
OPER	0.805***	0.459	1371.069	0.796***	0.476**	–0.164	1371.132
	(0.000)	(0.117)		(0.000)	(0.038)	(0.869)	
CHAD	–0.084	0.142	–747.436	–0.084	0.124	0.093	–747.435
	(0.180)	(0.261)		(0.181)	(0.638)	(0.946)	
FAZ	–0.137*	0.706***	–1187.282	–0.136	0.705***	–0.040	–1187.148
	(0.094)	(0.000)		(0.108)	(0.000)	(0.713)	

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

5. Conclusion, Implications, and Future Research

This study examined the long-memory properties of high- and low-carbon intensity ETFs using ARFIMA-GARCH, ARFIMA-FIGARCH, and ARFIMA-HYGARCH models. The findings reveal distinct differences in return predictability and volatility characteristics across ETF types, offering both theoretical insights and practical implications for sustainable finance and time-series modeling.

First, the study provides empirical evidence supporting the existence of long-memory processes in ETF returns, particularly among high-carbon intensity funds such as CHIU, XLU, and VPU. Many of these ETFs exhibited significant ARFIMA structures in their conditional mean processes, suggesting predictability in returns. Meanwhile, several low-carbon ETFs (e.g., TZA and CHAD) demonstrated stronger volatility persistence and anti-persistent return behavior, particularly when modeled with ARFIMA-HYGARCH.

Second, the results indicate volatility clustering in both ETF groups, with lagged conditional variances playing a more pronounced role than lagged returns. This aligns with the findings of [11], emphasizing the importance of volatility dynamics in financial forecasting. While the double long-memory effect—simultaneous persistence in both returns and volatility was not universally present, selected ETFs did exhibit partial long memory in both domains.

Third, the discovery of anti-persistent characteristics, especially among low-carbon and inverse ETFs, suggests a mean-reverting nature inconsistent with weak-form market efficiency. This contributes to the broader literature on inefficiencies in ESG-related investment vehicles and aligns with [21], who highlighted the complex and counterintuitive behavior of sustainable assets.

Fourth, model evaluation revealed that ARFIMA-HYGARCH consistently outperformed other specifications, particularly for low-carbon ETFs. This highlights the model's strength in capturing hyperbolic memory in volatility processes and supports its emerging role in sustainable investment research.

5.1. Practical implications

The study offers several actionable insights for investors and policymakers. For portfolio managers, the observed predictability in certain ETFs implies opportunities for active management strategies, especially when dealing with leveraged or inverse low-carbon ETFs that show high volatility memory. Investors can also use ARFIMA-HYGARCH models to enhance forecasting accuracy in ESG-themed portfolios, thus supporting long-term risk-adjusted performance.

From a policy perspective, the findings underscore the importance of considering product structure and regulatory oversight when promoting ESG-aligned investment instruments. The volatility behavior of low-carbon ETFs with anti-persistent traits may suggest instability in these assets, especially during turbulent market conditions. Policymakers should evaluate whether such fund structures deliver on their intended environmental and financial objectives.

5.2. Theoretical contributions

This research extends the existing literature by applying advanced long-memory models to an ESG-relevant asset class—carbon-intensive ETFs. While prior studies often focus on stock indices or corporate bond spreads, this paper introduces methodological innovation by using ARFIMA-HYGARCH to uncover nuanced dynamics in ETF behavior. These findings expand the theoretical understanding of market efficiency, volatility forecasting, and sustainability-linked financial modeling.

Furthermore, the results challenge the assumption that high-carbon investments are inherently riskier or less performant. Contrary to the common narrative, high-carbon ETFs in this study displayed lower volatility and better average returns than their low-carbon counterparts. This divergence from established ESG return expectations highlights the need for more granular and model-driven analysis in sustainable finance.

5.3. Limitations

Several limitations are acknowledged. First, the relatively short time series (March 2020 to September 2021) may limit the ability to detect structural breaks, especially related to major events such as the COVID-19 pandemic. While this period includes elevated market stress, longer datasets would allow for more robust analysis of pre- and post-shock behavior.

Second, although ARFIMA-based models were effective in this study, the exclusion of other fractional models such as Fractionally-integrated Asymmetric Power Autoregressive Conditional Heteroscedasticity (FIAPARCH) and Fractionally-integrated Exponential Generalized Autoregressive Conditional Heteroscedasticity (FIEGARCH) may limit comparative robustness. Including these models in future work could offer further insight into the memory dynamics of ETF volatility.

Third, carbon intensity classification was based on ETFdb.com ratings. While a credible source, incorporating additional ESG ratings or blending multiple scoring systems could provide a more comprehensive framework. Lastly, the preliminary step in the methodology is where the variance ratio test of Lo and MacKinlay can be applied to evaluate weak-form market efficiency.

5.4. Future research directions

Building on this study, future research can explore several promising directions. First, the models applied here could be tested across different asset classes, including green bonds, ESG mutual funds, or commodity ETFs. This would help assess the generalizability of the results and enhance model calibration across asset types.

Second, extending the analysis to other geographic markets—such as emerging economies or European ESG funds—would broaden the applicability of the findings. Different regulatory and policy contexts could influence carbon-transition risk pricing and volatility characteristics.

Third, incorporating macroeconomic variables (e.g., interest rates, inflation, carbon pricing policy changes) may help isolate the drivers behind observed memory dynamics. Doing so would allow for more targeted forecasting strategies and improve portfolio resilience under shifting economic conditions.

Lastly, future work may consider real-time applications, such as algorithmic trading strategies or ESG score-based portfolio rebalancing, to bridge the gap between academic modeling and investment practice.

This study contributes to a growing body of knowledge at the intersection of ESG investing, volatility modeling, and time-series econometrics. By combining theoretical insights with practical recommendations, it aims to inform both academic research and responsible investment decision-making.

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Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The data that support this work are available upon reasonable request to the corresponding author.

Author Contribution Statement

John Francis Diaz: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration. **Florian Gerth:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – review & editing. **Michael Young:** Conceptualization, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization, Project administration.

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