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Persistence in Stock Returns: Robotics and AI ETFs Versus Other Assets

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Abstract

This paper examines the long-memory properties of the returns of exchange-traded funds (ETFs) that provide exposure to companies operating in the fields of artificial intelligence (AI) and robotics listed on the US market, along with other assets such as the WTI crude oil price (West Texas Intermediate), Bitcoin, the S&P 500 index, 10-year US Treasury bonds, and the VIX volatility index. The data frequency is daily and covers the period from 1 January 2023 to 23 June 2025. The adopted fractional integration framework is more general and flexible than those previously used in related studies and allows for a detailed assessment of the degree of persistence in returns. The results indicate that all return series exhibit a high degree of persistence, regardless of the error structure assumed, and that, in general, a linear model adequately captures their dynamics over time. These findings suggest that newly developed AI- and robotics-themed ETFs do not provide investors with additional hedging or diversification benefits compared to more traditional assets, nor do they create new challenges for policymakers concerned with financial stability.

Keywords: persistence; fractional integration; long memory; trends; robotics ETFs; AI ETFs

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1. Introduction

In financial markets, investment strategies constantly change as a result of innovation, which has improved risk management and the efficiency of financial services, reduced transaction costs, and boosted capital flows and global economic growth (Frame & White, 2004). Exchange-traded funds (ETFs) incorporating artificial intelligence (AI) are undoubtedly the most notable among recent innovations.

With the rise of AI, investors are increasingly turning to AI-driven ETFs to gain exposure to this rapidly expanding sector while maintaining traditional portfolio diversification benefits (Valle-Cruz et al., 2024). These ETFs hold shares of companies active in AI technologies, rather than using AI algorithms for their investment decisions. Despite growing investor interest, research on AI-driven ETFs remains limited. According to Li et al. (2023), AI as a financial tool is used to optimize portfolios, assess risks, and anticipate market developments through its advanced information-processing capabilities. R. Chen and Ren (2022) analyzed the performance of funds that integrate AI into their investment processes.

Moreover, Poutachidou and Koulis (2025) showed that for ETFs specializing in AI technologies, asset selection contributes more to performance than active management strategies, while C.-C. Wu and Chen (2022) found that ETFs labeled "AI" generally generate positive abnormal returns.

Financial time series are very often modeled as long-memory processes to capture the behavior of both returns and volatility and gain a better understanding of how these can influence portfolio investment decisions. In particular, Granger and Joyeux (1980), as well as Hosking (1981), introduced the ARFIMA model (Autoregressive Fractionally Integrated Moving Average) in the early 1980s. Subsequently, Baillie et al. (1996) extended this framework in the 1990s by developing the FIGARCH (Fractionally Integrated Generalized Autoregressive Conditional Heteroskedasticity) model to analyze the dynamics of the conditional variance. The major advantage of such models is that they allow the differencing parameter to take any real values, including fractional ones, and therefore offer greater flexibility compared to conventional ARIMA and GARCH models. However, despite the growing interest of investors in ETFs, research focusing on the presence of long memory in the returns on these financial instruments remains limited (see Hussain & Chen, 2024; J.-H. Chen & Huang, 2023; Malinda & Chen, 2016; J.-H. Chen & Diaz, 2013; Yavas & Rezayat, 2016).

This paper aims to analyze the long-memory and persistence properties of the returns of exchange-traded funds (ETFs) focused on companies involved in the development and adoption of artificial intelligence (AI) and robotics-related technologies, including the Global X Artificial Intelligence & Technology (AIQ), ROBO Global Artificial Intelligence (THNQ), and Robotics (ROBT) ETFs, as well as other assets such as the price of West Texas Intermediate (WTI) crude oil, Bitcoin (BTC), the S&P 500 Index, 10-year U.S. Treasury bonds, and the VIX Volatility Index. The analysis is based on daily data covering the period from 1 January 2023 to 23 June 2025. Both linear and nonlinear fractional integration models are estimated, accounting for different error structures and using both raw and logarithmic return series. Although successful portfolio diversification strategies depend on correlations between assets as well, shedding light on differences in terms of the degree of persistence is also useful to decide on the optimal composition of a portfolio. Therefore, the results of the analysis will yield for investors valuable insights into suitable diversification strategies and for policy makers a better understanding of the impact of sector ETFs on financial stability.

The paper is structured as follows: Section 2 reviews the relevant literature; Section 3 provides a data description; Section 4 outlines the empirical framework; Section 5 presents the empirical results; Section 6 offers some concluding remarks.

2. Literature Review

The relevant literature comprises three main strands. The first includes a number of studies focusing on the persistence of returns and volatility of exchange-traded funds (ETFs), particularly in contexts of high market volatility (Hadad et al., 2025; C.-C. Wu & Chen, 2022; Karoui et al., 2024; Nguyen et al., 2025; Agapova et al., 2025).

Yavas and Rezayat (2016) studied volatility persistence among US, European, and emerging market ETFs using multivariate autoregressive (MARMA) and GARCH models. Their results show that volatility persists over time and is transmitted only between certain markets. Hussain and Chen (2024) analyzed the interdependencies between financial, technology, and FinTech ETFs and the stock index using ARMA-GARCH and ARMA-EGARCH models. They found contagion effects, asymmetric leverage, and a positive relationship between volatility and trading volumes. E.-C. Wu (2025) showed that high ETF turnover rates significantly increase volatility in the Taiwanese stock market, an effect amplified by liquidity and the presence of noisy traders.

A second strand incorporates the concepts of long memory and structural breaks into the analysis of ETF behavior. Malinda and Chen (2022) analyzed consumer ETFs and showed that only the gaming and consumer goods sectors exhibited long memory in volatility, while highlighting the influence of multiple structural breaks generating asymmetric effects. F.-Y. Chen and Chen (2023) examined the long memory properties and structural breaks of various carbon indices, ETFs, ETNs, and futures contracts using ARFIMA-FIGARCH models and the Iterative Cumulative Sum of Squares (ICSS) algorithm. Their results reveal the presence of long memory and several structural breaks linked to major economic events. Similarly, J.-H. Chen and Diaz (2013) demonstrated that non-green ETFs exhibit long memory processes in volatility, confirming the persistence of dynamics in certain market segments. Other studies (J. H. Chen & Malinda, 2014; J.-H. Chen & Huang, 2014) applied ICSS (Iterative Cumulative Sum of Squares) and ARFIMA-FIGARCH to travel and tourism indices and volatility index (VIX) ETFs, revealing that nearly 90% of indices experience multiple structural breaks and that long memory is particularly pronounced in the United States. Lin et al. (2024) used MGARCH models (CCC, DCC, and BEKK) to assess the impact of sector and carbon ETFs on returns and volatility, highlighting dynamic short- and long-term correlations. J.-H. Chen and Hsieh (2025) applied ARFIMA, FIGARCH, and HYGARCH to carbon and energy ETFs, confirming long memory and showing that the ARFIMA-HYGARCH model is superior to ARFIMA-FIGARCH in capturing this persistence while incorporating multiple market indices.

G. G. Rompotis (2025) studied the performance persistence of 332 US-listed equity ETFs, revealing some stability in returns over time. Other studies, such as Mateus et al. (2020) on 152 smart beta ETFs over a period from June 2000 to May 2017, showed that the relative performance of winners and losers persists from one year to the next. G. Rompotis (2023a) examines the performance and performance persistence of US-listed ETFs that are exposed to European stock markets, showing that the performance of these ETFs does not persist. G. Rompotis (2023b) emphasizes a reversion behavior of daily (and partially) weekly returns of US-listed ESG ETFs. G. Rompotis (2024) shows that in the case of ETFs listed in Australia, performance returns from one year to the next.

The third strand combines econometrics and machine learning methods to improve ETF forecasting. Petrosino et al. (2025) sought to improve the prediction of financial asset volatility, which is essential for assessing the risk associated with returns, by combining traditional econometric methods and deep learning techniques through a hybrid GARCH-TFT (GARCH temporal fusion transformer) model applied to ETFs composed of S&P 500 assets. Their results showed that this hybrid model outperformed others in predicting the Garman-Klass (GK) volatility estimator and that its performance was comparable to that of the standalone TFT for historical volatility, highlighting the potential of combining econometric approaches and deep learning to increase predictive accuracy in volatile financial markets. Gheorghe et al. (2025) used quantile-quantile regression (QQR) and wavelet coherence analysis (WCO) to examine the asymmetric responses of artificial intelligence (AI) and ESG-related thematic ETFs to geopolitical and financial uncertainties. Their results show that ESG ETFs are more resilient in times of extreme uncertainty, while AI-focused ETFs perform better in moderate risk environments but are more vulnerable to systemic stress. Ji et al. (2024) estimated a Time-Varying Parameter VAR (TVP-VAR-DY) model and showed that gold is an effective hedge against fluctuations in energy ETFs. Kang et al. (2021), through time-frequency analysis, identified directional links between US equity ETFs, gold, oil, the stock market, and uncertainty indices, showing that oil exerts a stronger influence than gold on ETFs, regardless of the time horizon.

Most previous studies on ETFs have used volatility models such as GARCH models (E.-C. Wu, 2025; Hussain & Chen, 2024) or frequency domain approaches (Gheorghe et al., 2025), while none have estimated fractional integration to analyze return persistence, even though this approach results in a better understanding of long-term dependencies than standard ARMA or GARCH models. For this reason, the present study seeks to fill this gap by applying fractional integration to different asset classes and obtaining an extensive set of results with important implications for investors and policy makers.

3. Data and Descriptive Statistics

This study uses daily data from three US-listed exchange-traded funds (ETFs) that offer exposure to companies in the artificial intelligence (AI) and robotics sectors. The Global X Artificial Intelligence & Technology ETF (AIQ) invests in companies engaged in the development and application of AI technologies in various sectors, such as machine learning and big data analytics. The ROBO Global Artificial Intelligence ETF (THNQ) includes global companies operating in the AI ecosystem and its technological infrastructure. The Robotics ETF (ROBT) focuses on companies in the technology, industrial, and related sectors contributing to the advancement of AI and robotics. These ETFs are studied alongside other traditional asset classes, including crude oil (WTI), Bitcoin (BTC), the S&P 500 Index, the 10-year US Treasury bond, and the VIX Volatility Index, also known as the "fear index." The latter measures market expectations for the future volatility of the S&P 500 over a 30-day horizon. Calculated from S&P 500 option prices, the VIX reflects the level of uncertainty and investor sentiment. In this study, it is used to identify periods of stress and increased volatility that may influence the persistence of returns for ETFs and other asset classes. The three selected ETFs were chosen because of their large market capitalization and high liquidity, which make them the main investment instruments in the fields of artificial intelligence and robotics. Analyzing these ETFs therefore provides valuable insights into the persistence of returns in these sectors. The sample period spans from 1 January 2023 to 23 June 2025, and the data were obtained from https://finance.yahoo.com/ (accesed on 23 June 2025)

For the estimation stock returns are calculated as follows:

$$R_t = \mathrm{Log}\left(\frac{P_t}{P_{t-1}}\right),$$

where P_t stands for the stock price at time t.

Table 1 presents descriptive statistics for AI and robotics-related sector ETFs, as well as for the other assets considered in this study. All average returns are positive, except for those of the oil market (WTI) and the VIX volatility index. Bitcoin (BTC) exhibits the highest average return (20.43%), whilst the VIX index has the highest standard deviation (6.382), suggesting that it is the most volatile series. This reflects the nature of the VIX, which measures expected market volatility and investor uncertainty in the US stock market. The skewness test results indicate that, with the exception of oil (WTI) and US Treasury bonds, all assets exhibit strictly positive skewness (>0). This implies that their return distributions are skewed to the right, with a longer right tail, suggesting the potential for higher returns and relatively strong resilience to market volatility. By contrast, oil (WTI) and US Treasury bonds exhibit negative skewness, with values of −0.794 and −0.324, indicating left-skewed distributions and greater vulnerability to large negative returns. The marked kurtosis of most assets reveals the presence of fat tails. This evidence implies that the distributions of returns deviate from normality and motivates the estimation of models with different assumptions about the errors. The results of the Jarque–Bera test reject the null hypothesis of normality for all return series. Finally, the ADF (Augmented Dickey–Fuller) test confirms that all return series are stationary at the 1% significance level.

Table 1. Descriptive Statistics.

	Mean	Min.	Max.	S. Dev.	Skewness	Kurtosis	JB	ADF
WTI	−0.0223	−13.925	8.708	1.748	−0.794	9.053	1475.2 ***	−10.182 ***
BTC	0.2043	−8.933	11.275	2.522	0.403	5.247	214.58 ***	−9.5046 ***
US 10y	0.0056	−6.242	4.834	1.353	−0.324	5.152	190.31 ***	−10.07 ***
SP500	0.0498	−6.161	9.089	0.827	0.549	24.207	16,985 ***	−10.497 ***
ROBT	0.0276	−6.769	11.015	1.229	0.277	12.325	3287 ***	−9.7972 ***
AIQ	0.0814	−7.232	11.503	1.181	0.362	15.628	6026.4 ***	−9.5437 ***
THNQ	0.0755	−7.038	12.031	1.330	0.248	12.579	3465.7 ***	−9.416 ***
VIX	−0.0098	−44.245	55.411	6.382	1.340	19.809	10913 ***	−10.815 ***

Notes: Max/Maximum, Min/Minimum, S.D./Standard Deviation, Skewness/Skewness, Kurt/Kurtosis. The Jarque–Bera (J.B.) statistic tests the null hypothesis that a time series is normally distributed by examining its first two moments skewness and kurtosis. Under the null hypothesis, the statistic follows a chi-square distribution with two degrees of freedom. The Augmented Dickey–Fuller (ADF) test is a unit root test used to assess the stationarity of a series. At the 1% significance level, the ADF test indicates stationarity for the following assets: Global X Artificial Intelligence & Technology ETF (AIQ), ROBO Global Artificial Intelligence ETF (THNQ), Robotics ETF (ROBT), crude oil (WTI), Bitcoin (BTC), the S&P 500 index, the US 10-Year Treasury bond, and the CBOE Volatility Index (VIX). *** indicates significance at the 1% level.

4. Methodology

The methodology is based on fractional integration. This is a time series technique that basically suggests that the degree of differencing required to make a series stationary $I(0)$ can be a fractional value. In other words, assuming that $\{u(t), t = 0, \pm 1, \ldots\}$ is a covariance stationary $I(0)$ process, defined as a process where the infinite sum of its autocovariances is finite (e.g., a white noise or a stationary AutoRegressive Moving Average, ARMA.type of process), we say that a process is integrated of order d or $I(d)$ if it can be expressed in terms of

$$(1-L)^{d}\, x(t) = u(t), \quad t = 0, \quad \pm 1, \quad \ldots, \tag{1}$$

where L is the lag operator, i.e., $Lx(t) = x(t-1)$, and d is a given real value. Note that the standard specifications in the literature examine the cases of $d = 0$ ($I(0)$ or short memory) versus $d = 1$ (unit roots) not allowing for fractional degrees of differentiation. In the 1980s, Granger (1980) and Granger and Joyeux (1980) introduced the $I(d)$ processes based on the observation that many series seemed to be over-differenced once they were first differenced. This specification is more general and it includes, for example, the cases of stationary long memory processes, if $0 < d < 0.5$, and nonstationary though mean reverting processes if $0.5 \leq d < 1$. In addition, noting that the polynomial in L in (1) can be expressed in terms of its Binomial expansion,

$$(1-L)^{d} \;=\; \sum_{j=0}^{\infty} \binom{d}{j} (-1)^{j} L^{j} \;=\; 1 - d\,L + \frac{d\,(d-1)}{2} L^{2} - \ldots \tag{2}$$

Hence, $x(t)$ can be expressed as:

$$x(t) \;=\; d\,x(t-1) \;-\; \frac{d\,(d-1)}{2}\, x(t-2) \;+\; \ldots \;+\; u(t). \tag{3}$$

In this context, d indicates the degree of persistence of the series where a higher value of d indicates a higher degree of dependence between the observations.

The second model specification allows for weak time dependence in the error term $u(t)$; however, instead of assuming a classical Autoregressive Moving Average (ARMA) process, we employ a non-parametric approach approximating AR structures which is based on a spectral density function given by:

$$f\left(\lambda;\sigma^2\right) = \frac{\sigma^2}{2\pi} exp\left(2\sum_{r=1}^{m} \tau_r cos(\lambda r)\right), \tag{4}$$

where σ^2 stands for the variance of the error term, and m is a parameter corresponding to the last of the Fourier frequencies.

Bloomfield (1973) showed that the logarithmic form of the above function approximates fairly well the behavior of the density function of autoregressive (AR) processes of high orders without requiring many parameters. This model is highly suitable for fractional differentiation, and, in particular, in the context of the tests of Robinson (1994) used in this application (see, e.g., Gil-Alana, 2004, 2008) and, in contrast to the AR model, is stationary for all values of τ, while producing autocorrelations that decay at an exponential rate as in the AR case. Note that since the main purpose of this work is the analysis of long run persistence through the differencing parameter d, the model of Bloomfield removes the weak dependence structure to describe the short-run dynamics of the data.

Finally, we allow for nonlinearities using a model incorporating Chebyshev polynomials in time, which is specified as follows:

$$y(t) \;=\; \sum_{i\,=\,0}^{m} \theta_i \, P_{iT}(t) \;+\; x(t)\,, \qquad t = 1,\, 2,\, \ldots, \tag{5}$$

where $x(t)$ is defined as in Equation (1), m denotes the number of coefficients of the Chebyshev polynomials, and $P_{i,T}(t)$ is defined as:

$$P_{0,T}(t) = 1, P_{i,T}(t) = \sqrt{2}\, \cos(i\,\pi\,(t-0.5)/T), \qquad t = 1, 2, \ldots, T; \qquad i = 1, 2, \ldots. \tag{6}$$

If m = 0 the model includes only an intercept, whilst for m > 0, it becomes nonlinear—the higher m is, the less linear the deterministic component becomes. A detailed description of these polynomials can be found in Hamming (1973), Smyth (1998), and Bierens (1997); Tomasevic et al. (2009) showed that they can approximate highly nonlinear trends with polynomials of a relatively low order.

In all cases we implement versions of Robinson's (1994) tests widely used in empirical applications. We test the null hypothesis:

$$H_o\text{: } d = d_o, \tag{7}$$

for any real value d_o, first in the model given by Equation (1). Under H_o (5), the residuals in (1) are:

$$\hat{u}(t) \;=\; \hat{y}(t) - \hat{\alpha}\,(1-L)^{d_o}\hat{1}(t) - \hat{\beta}\,\hat{t}(t),$$

where $\hat{\alpha}$ and $\hat{\beta}$ are the OLS estimates of the intercept and the time trend, respectively, and $\hat{y}(t) = (1-L)^{d_o}y(t)$; $\hat{1}(t) = (1-L)^{d_o}1$, and $\hat{t}(t) = (1-L)^{d_o}\,t$; and the periodogram of $\hat{u}(t)$ is given by:

$$I(\lambda_j) = \frac{1}{2\pi T}\left|\sum_{t=1}^{T} \hat{u}(t)\, e^{i\,\lambda_j t}\right|^2, \; with\ \lambda_j = \frac{2\pi j}{T},\; j = 0, 1, \ldots, T-1.$$

The test statistic is then:

$$\hat{r}_1 = \left(\frac{T}{\widehat{\hat{A}_1}}\right)^{1/2} \frac{\hat{a}_1}{\hat{\sigma^2}},$$

where T is the sample size, $\hat{\sigma^2}$ is the variance of the error term, and

$$\hat{a}_1 = \frac{-2\pi}{T}\sum_{t=1}^{T-1}\psi(\lambda_j)I(\lambda_j) \quad \text{and} \quad \hat{A}_1 = \frac{2}{T}\sum_{t=1}^{T-1}\psi(\lambda_j)^2,\ \psi(\lambda_j) = log\left|sin\frac{\lambda_j}{2}\right|.$$

For the second specification, the only change is in the nature of $u(t)$ in (1) which is now autocorrelated, and then, the test statistic becomes:

$$\hat{r}_2 = \left(\frac{T}{\widehat{\hat{A}_2}}\right)^{1/2}\frac{\hat{a}_2}{\hat{\sigma^2}},$$

with $\hat{a}_2 = \frac{-2\pi}{T}\sum_{t=1}^{T-1}\psi(\lambda_j)g^{-1}(\lambda_j;\ \hat{\tau})\ I(\lambda_j)$;

$$g(\lambda_j;\ \hat{\tau}) = exp(2\sum_{j=1}^{q}\hat{\tau}_j cosj\lambda);\ \text{and}\hat{\tau} = arg\ min_\tau\ \hat{\sigma^2},\ where\hat{\sigma^2} = \sigma^2(\tau).$$

$$\hat{A}_1 = \frac{2}{T}\sum_{t=1}^{T-1}\psi(\lambda_j)^2\left(\sum_{t=1}^{T-1}\psi(\lambda_j)\ \hat{\varepsilon}(\lambda_j)^T\right)^{-1}\left(\sum_{t=1}^{T-1}\hat{\varepsilon}(\lambda_j)\ \psi(\lambda_j)^T\right)$$

with $\varepsilon(\lambda_j) = 2\ cos\ (\lambda l)$.

Finally, the third (nonlinear) approach is based on the following statistic:

$$\hat{r}_3 = \left(\frac{T}{\widehat{\hat{A}_3}}\right)^{1/2}\frac{\hat{a}_3}{\hat{\sigma^2}},$$

where $\hat{a}_3$ and $\hat{A}_3$ are as in $\hat{a}_1$ and $\hat{A}_1$ but using the residuals $\hat{u}(t)$ based on the nonlinear specification.

Under very mild regularity conditions, it can be proved that:

$$\hat{r}_i \quad \rightarrow_{T\rightarrow\infty}\ N(0,1), \quad \text{for } i = 1,\ 2,\ \text{and } 3.$$

(see Robinson, 1994). Despite the asymptotic nature of the tests, finite sample critical values were also computed (see Gil-Alana, 1999) and the results in terms of the confidence intervals for the non-rejection values of d_o were almost identical under the two scenarios. This is not surprising given the large number of observations used in the application carried out in the following section.

5. Empirical Results

Table 2 reports the estimates of the coefficients for each series based on Equation (1). Specifically, column 2 shows the estimated values of d along with their associated 95% confidence bands, and columns 3 and 4 the estimates of the intercept (α) and of the coefficient on the time trend (β) with the corresponding t-values.

It is observed that for the three AI series, the estimates of the fractional differencing parameter d are very close to 1. This indicates that shocks affecting these ETFs have high persistence, implying limited short-term market efficiency and potential opportunities for long-term strategic investors. Among the AI ETFs, AIQ exhibits a significant positive time trend, while only the intercept is significant for THNQ and ROBT, indicating that long-term growth is more pronounced for AIQ. As for the other four series, the d estimates are slightly lower, but the null hypothesis of a unit root cannot be rejected in three cases, suggesting that these markets also exhibit significant persistence. BTC is the only series exhibiting mean-reverting behavior, with the confidence interval for d bing less than 1, indicating that the shocks are temporary. A positive time trend is observed for WTI and the S&P 500. Finally, for the VIX, the d estimate is equal to 0.86, and there is clear evidence of mean reversion, while the time trend is not significant, indicating that volatility shocks are transitory and short-lived.

Table 2. Equation (1) estimates with white noise errors and returns.

Series	*d* (95% Band)	Intercept (t-Value)	Time Trend (t-Value)
AIQ	0.98 (0.93, 1.03)	20.082 (51.88)	0.024 (2.12)
THNQ	1.00 (0.95, 1.05)	26.299 (47.84)	---
ROBT	0.99 (0.94, 1.04)	35.727 (69.17)	---
BTC	0.94 (0.90, 0.99)	80.189 (62.86)	---
WTI	0.97 (0.92, 1.03)	16,529.82 (10.41)	97.65 (2.70)
S&P 500	0.95 (0.91, 1.01)	3837.39 (90.56)	2.401 (2.34)
US 100	0.97 (0.93, 1.02)	3.875 (71.28)	---
VIX	0.86 (0.81, 0.91)	21.622 (14.49)	---

Notes: Column 2 reports the estimates of d with the corresponding 95% confidence intervals, columns 3 and 4 those of the intercept and the time trend, respectively, with the corresponding t-statistics.

Table 3 reports the results for the logged series. The results are fairly similar to those reported for the original data. Specifically, for most of the assets the estimated values of d are close to 1 but the confidence bands indicate that the unit root null hypothesis cannot be rejected in any case, including now BTC. For VIX, the value of d is slightly higher but it still supports the hypothesis of mean reversion, indicating that the effects of shocks are transitory and allow the market to return to its long-term equilibrium. This behavior illustrates the regulatory role of market volatility, providing essential information for risk management.

Table 3. Equation (1) estimates with white noise errors and logged returns.

Series (logs)	*d* (95% Band)	Intercept (t-Value)	Time Trend (t-Value)
AIQ	0.98 (0.94, 1.04)	3.000 (254.34)	0.0008 (2.33)
THNQ	1.00 (0.95, 1.05)	3.268 (245.76)	---
ROBT	0.99 (0.94, 1.04)	3.575 (291.22)	---
BTC	0.98 (0.94, 1.03)	9.716 (385.68)	0.002 (2.75)
WTI	0.96 (0.91, 1.02)	4.384 (251.74)	---
S&P 500	0.96 (0.91, 1.01)	8.752 (1000.75)	0.005 (2.32)
US 100	0.97 (0.92, 1.02)	1.354 (100.34)	---
VIX	0.92 (0.87, 0.98)	3.075 (48.72)	---

Notes: Column 2 reports the estimates of d with the corresponding 95% confidence intervals, columns 3 and 4 those of the intercept and the time trend, respectively, with the corresponding t-statistics.

Tables 4 and 5 reports the results obtained when allowing for weak autocorrelation and using the raw data and the logged ones, respectively.[1] It can be seen in the former that for the AI series once again the estimated values of d are around 1 (0.99 for AIQ and THNQ, and 1.00 for ROBT), in indicating near-unit-root behavior and strong long-memory persistence. The time trend is now significant for AIQ and THNQ, suggesting that these ETFs exhibit both persistent shocks and a gradual upward trend over time. This persistence implies that short-term market efficiency is limited. As for the other series, the estimated values of d range between 0.94 (WTI) and 0.98 (BTC) but the unit root null hypothesis cannot be rejected in any case, whilst the time trend is now significant for BTC and S&P500, indicating a long-term upward trajectory in these markets. Finally, the estimated order of integration for the VIX is 0.88 and the upper limit of the confidence interval is 1, providing evidence of mean-reverting behavior while still exhibiting moderate persistence. These results suggest that the long-term dynamics of AI ETFs are similar to those of traditional assets, providing limited additional diversification.

Table 4. Equation (1) estimates with autocorrelated errors and returns.

Series (Original)	*d* (95% Band)	Intercept (t-Value)	Time Trend (t-Value)
AIQ	0.99 (0.91, 1.09)	20.087 (51.86)	0.024 (2.00)
THNQ	0.99 (0.91, 1.09)	26.274 (47.77)	0.028 (1.65)
ROBT	1.01 (0.91, 1.09)	35.707 (69.14)	---
BTC	0.98 (0.91, 1.08)	16,522.78 (10.36)	98.058 (2.10)
WTI	0.94 (0.84, 1.06)	88.107 (62.98)	---
S&P 500	0.95 (0.88, 1.05)	3837.39 (90.56)	2.401 (2.34)
US 100	0.97 (0.89, 1.05)	3.875 (71.28)	---
VIX	0.88 (0.78, 1.00)	21.637 (14.42)	

Notes: Column 2 reports the estimates of d with the corresponding 95% confidence intervals, columns 3 and 4 those of the intercept and the time trend, respectively, with the corresponding t-statistics.

Table 5. Equation (1) estimates with autocorrelated errors and logged returns.

Series (logs)	*d* (95% Band)	Intercept (t-Value)	Time Trend (t-Value)
AIQ	0.99 (0.91, 1.09)	2.999 (254.22)	0.0008 (2.07)
THNQ	0.99 (0.92, 1.09)	3.268 (245.76)	0.0007 (1.70)
ROBT	1.00 (0.92, 1.11)	3.575 (291.22)	---
BTC	1.04 (0.96, 1.13)	9.715 (386.38)	0.002 (1.92)
WTI	0.96 (0.85, 1.05)	4.384 (251.73)	---
S&P 500	0.95 (0.87, 1.06)	8.252 (1001.49)	0.0005 (2.48)
US 100	0.96 (0.90, 1.05)	1.354 (100.31)	---
VIX	0.86 (0.77, 0.96)	3.073 (49.44)	---

Notes: Column 2 reports the estimates of d with the corresponding 95% confidence intervals, columns 3 and 4 those of the intercept and the time trend, respectively, with the corresponding t-statistics.

Table 5 shows that the results using the logged values are almost identical to those based on the original data in the case of the AI series; as for the other series, the main differences are the estimate of d for BTC, which is now much higher (1.04—although the unit root null again cannot be rejected), and for VIX (0.86), which now suggests the presence of mean reversion and a faster adjustment to new information.

Finally, Table 6 presents the nonlinear estimates based on Equation (5) assuming white noise errors and using returns as the dependent variable (virtually identical results were obtained under the assumption of autocorrelated errors and with logged returns). The estimates of d are very close to those yielded by the linear specification, suggesting that the observed long-memory dynamics are broadly robust to the inclusion of nonlinearities in the model. There is some evidence of nonlinearities only in the case of AIQ, with only one nonlinear coefficient being statistically significant in this case. For the other four series, the estimates of d are once again around 1 and some evidence of nonlinear structures is found in the cases of BTC and S&P500; finally, VIX exhibits mean reversion but not nonlinear trends.

Table 6. Equation (3) nonlinear estimates with white noise errors and returns.

Series	D (95% Band)	θ_1 (t-Value)	θ_2 (t-Value)	θ_3 (t-Value)	θ_4 (t-Value)
AIQ	0.98 (0.94, 1.03)	3.321 (19.46)	−0.172 (−1.68)	−0.027 (−0.51)	0.037 (1.04)
THNQ	1.00 (0.95, 1.05)	3.562 (16.34)	−0.182 (−1.38)	−0.054 (−0.82)	−0.043 (−0.98)
ROBT	1.00 (0.94, 1.04)	3.617 (17.74)	−0.041 (−0.33)	−0.027 (−0.44)	−0.040 (−0.97)
BTC	0.98 (0.94, 1.03)	10.521 (27.76)	−0.490 (−2.15)	−0.025 (−0.22)	0.155 (1.98)
WTI	0.96 (0.89, 1.03)	4.373 (20.12)	0.043 (0.33)	−0.050 (−0.73)	0.0005 (0.01)
S&P 500	1.01 (0.91, 1.06)	8.460 (58.12)	−0.093 (−1.05)	0.071 (1.67)	−0.075 (−2.58)
US 100	0.96 (0.91, 1.02)	1.498 (8.91)	−0.032 (−0.31)	−0.041 (−0.78)	−0.033 (−0.91)
VIX	0.92 (0.86, 0.98)	2.909 (4.72)	−0.031 (−0.08)	0.143 (0.71)	0.012 (0.08)

Notes: The second column repots the estimates of d with the associated 95% confidence intervals. The other columns display the estimated coefficients of the Chebyshev polynomials with the corresponding t-values.

The near-unity estimates of the fractional differencing parameter (d = 1) indicate a high degree of persistence in the returns of AI-related ETFs. This implies that in their case prices adjust slowly to the arrival of new information; this represents evidence of market inefficiency giving rise to arbitrage opportunities, at least in the short run. Furthermore, the closeness in terms of the estimated values of d between AI-linked ETFs and other asset classes, notably the S&P 500 and BTC, suggests similar long-memory dynamics for all those assets, which limits the opportunities for portfolio diversification.

6. Conclusions

Financial innovation has become increasingly important in recent decades and has led to the development of new financial instruments and the design of new investment strategies. ETFs focusing on AI and robotics have become particularly popular and have attracted considerable attention as possible hedging and diversification tools. Their emergence has also generated a new literature examining their behavior in comparison to that of more traditional assets. However, none of the existing studies have used fractional integration methods to shed light on the respective persistence properties of those financial instruments.

The aim of the present paper is to fill this gap in the literature and to detect any significant differences between the different asset classes considered in terms of the degree of persistence of their returns. More specifically, we estimate both linear and nonlinear fractional integration models for returns, allowing for different error structures, and using both the raw data and the logged ones. Interestingly, the different specifications produce very similar results. Specifically, the evidence suggests that all returns series examined are highly persistent, regardless of the error structure assumed, and that, in general, a linear model is appropriate to capture their evolution over time. This points to market inefficiencies, implying the existence of riskless profit opportunities that can be exploited through appropriately designed trading strategies before prices revert to their long-run equilibrium. The fact that there are no significant differences in the behavior of returns for the various assets considered also indicates that the newly developed ones do not offer to investors additional hedging and diversification opportunities compared to more traditional ones.

Our findings also have policy implications: they essentially suggest that the new financial landscape resulting from the creation of additional financial instruments does not pose significant new challenges to policy makers whose responsibility it is to maintain financial stability. Specifically, in terms of monitoring systemic risk, since no significant differences have been detected between the different asset classes in terms of the degree of persistence of their returns, standard monitoring tools still seem to be appropriate, despite the growing number of available financial instruments. However, it might be useful for policy makers to require more transparency and standardized reporting for thematic EFTs in order to assess more accurately their features and the possibility of risk transmission.

Finally, it should be acknowledged that our analysis has some limitations. In particular, the estimation of the long-memory parameter (d) may be sensitive to the sample size and the choice of estimation method, which could affect the robustness of the empirical results. Therefore, future research could also examine longer spans of data and use alternative estimators in addition to analyzing data for other markets as robustness checks. Another important issue not investigated in the present study is the possible presence of structural breaks as the high degree of persistence observed in the data may be a direct consequence of breaks that have not been taken into account. It should be noted that incorporating breaks imposes abrupt changes on the series and thus the approach followed in this paper, based on nonlinear Chebyshev polynomials in time, can be seen as a useful alternative. Nevertheless, future work could also carry out exogenous break tests to detect cases when parameters switch rather than evolve gradually.

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Note

[1] As a diagnostic check we tested for additional serial correlation in the residuals of the selected models. In particular, we performed tests of no serial correlation (Durbin, 1970; Godfrey, 1978) whose results supported the null of no time dependence in the selected models in all cases.

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