Modelling the Volatility of NFTs and Traditional Financial Assets using MGARCH Family Models

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Abstract

This paper examines the efficiency and asymmetric multiracial features of NFTs (Mana, Tezos), and traditional assets (EGX30, Oil index) using Asymmetric Multiracial Cross-Correlations Analysis covering the period from January 2020 to May 2021. Considering the full sample with a significant variation among asset classes. (Oil-Tezos) and (Mana-Tezos) is the most efficient.

Keywords

Volatility, NFTs, Traditional Financial Assets, and MGARCH

1. Introduction

Since their inception, the blockchain-based digital asset classes have received immense interest from investors and portfolio managers as an alternative investment platform. Along with other established traditional cryptocurrencies such as Bitcoin, Litecoin, Ripple, and Ethereum, new blockchain asset classes such as Decentralized Finance (DeFi) and Non-Fungible Tokens (NFTs) have made a considerable contribution to the asset market's recent expansion (Aharon & Demir, 2021; Alam, Chowdhury, Abdullah, & Masih, 2023; Maouchi, Charfeddine, & el Montasser, 2021; Yousaf & Yarovaya, 2022). Fundamentally, NFTs and DeFi differ from traditional cryptocurrencies as they are not virtual currency. Where NFTs are non-transferable cryptographic digital assets created by Ethereum smart contracts and can be sold and traded, the interchangeability of NFTs when comparing the other cryptocurrencies is very low (Karim, Lucey, Naeem, & Uddin, 2022; Q. Wang, Li, Wang, & Chen, 2021; Y. Wang, 2022). The NFTs and DeFi are relatively contemporary and unexplored asset classes, but their market capitalization has grown substantially as risk minimizing assets, particularly during the COVID-19 period. In the NFT space, the pandemic has increased demand for digital art and collectibles as the shift to remote work, and online commerce fueled interest in digital assets (Alam et al., 2023). The interest has driven up prices for some NFTs and has contributed to a general increase in the popularity of NFTs. In addition, the return on NFTs, which is considered uncorrelated with other assets, such as stocks, bonds, and commodities, because they are not tied to any underlying financial performance or revenue stream.

From 2014 through 2022, the NFTs and DeFi market and prices are influenced by various factors, including the development of blockchain technology, underlying protocols and products, the level of liquidity in the market, and shifts in investor sentiment toward the NFTs and DeFi ecosystem (Alam et al., 2023; Ko, Son, Lee, Jang, & Lee, 2022). NFTs gained widespread attention in the blockchain space in 2017 with the launch of the Ethereum network's ERC-721 standard (Wilson, Karg, & Ghaderi, 2021). In the early days of NFTs, the market was relatively small, with sales typically tens of thousands of dollars. However, the market for NFTs has seen tremendous growth since 2019, with some sales reaching millions of dollars in 2020. The first popular NFTs were CryptoKitties, a collectible game built on the Ethereum blockchain, and CryptoPunks, a set of 10,000 unique digital characters (Dowling, 2022a; Pinto-Guti´errez, Gait´an, Jaramillo, & Velasquez, 2022).

Furthermore, asymmetric price movement and spike of short-term risk spillover were observed during the COVID-19 period among NFTs, DeFi, cryptocurrencies, and other assets (Karim et al., 2022), therefore investor had to pay attention to the selection of efficient assets in portfolio construction. Moreover, the interest in asset allocation based on asset efficiency criteria has gained new momentum as the extreme events of the COVID-19 lockdown (Abdullah, Wali Ullah, & Chowdhury, 2022), followed by the Russia-Ukraine war, have triggered severe stress in the global financial markets.

In the light of the significance of volatility scaling patterns, we aim to examine the efficiency and multifractality of NFTs along with other traditional assets using Multivariate Generalized Autoregressive Conditional Heteroskedasticity (MGARCH). The traditional financial assets include crude oil, and EGX30. Our sample period ranges from January 2020 to May 2021, covering the starting date of the Covid-19 pandemic crisis (1/1/2020-

1/6/2021), and the starting date of the Crypto-Bubble crisis (1/1/2021-1/6/2021).

Our main findings show a considerable asymmetry in asset efficiency variation among the asset classes, where Oil-Tezos is the most efficient while the EGX30-Tezos is the least efficient. Before COVID-19, traditional asset (S&P 500) was the most efficient asset class, while during the COVID-19 period, traditional Asset (S&P 500) ranked second in terms of efficiency. Considering the entire sample period, NFTs (Tezos) is the most efficient asset class. The asymmetric spectrum result suggests NFTs is more sensitive to smaller events, large fluctuations dominating bull markets, and small fluctuations dominating bear markets.

The findings of this paper contribute to the two areas of literature focusing on the efficiency of financial and digital asset markets. Firstly, the empirical estimation of the MGARCH adds to the literature that estimates the properties of NFTs and traditional assets. Secondly, the findings of our study provide new evidence on possible cross-assets asymmetries in volatility movements between pre-and during-COVID-19 periods.

The rest of the paper is outlined as follows: Section 2 provides a brief literature review, Section 3 discusses the methodology and data of this study, Section 4 elaborates on the empirical findings, Section 5 concludes the study.

2. Literature review

The efficient market hypothesis (EMH) is a foundational theory of modern finance (Fama, 1970); EMH categorizes market efficiency into three levels based on how much accessible information is represented in asset price: strong, semi-strong, and weak. Investing in a financial instrument is deemed efficient in the weak form if market prices completely represent the available information. However, NFTs has unique characteristics as these asset classes are relatively new and still evolving, where returns and volatility are highly influenced by asymmetric market sentiment in a limited number of buyers and sellers and the success or failure of underlying protocols and products. In addition, behavioral biases such as artist popularity, herding, overconfidence, and overreaction can further affect the prices of these assets in ways that are not reflected in the underlying EMH.

Recent literature utilized MF-DFA to analyze multifractal noise, market volatility, and portfolio selection in general, to improve price predictability for portfolio diversification and optimization. Closely related to our paper, several recent studies focus on the multifractal features of stock (Chai, Chu, Zhang, Abedin, & Lucey, 2022; Mensi, Lee, Vinh Vo, & Yoon, 2021; Tiwari, Aye, & Gupta, 2019), commodities (Guo et al., 2021; Mensi, Vo, & Kang, 2022), foreign exchange (Diniz-Maganini, Rasheed, & Sheng, 2021) and cryptocurrencies (Bariviera, 2021; Cao & Xie, 2021; Chowdhury, Abdullah, & Masih, 2022; Kakinaka & Umeno, 2022). Concerning the efficiency property of assets, Mensi et al. (2021) analyze the efficiency of top crude oil-producing countries and consumer countries' stock markets. Their findings suggest a strong multifractality in a bull market and a decline in efficiency during the global financial crisis COVID-19.

In the review of the recent empirical literature, we look at studies that examine gold as an alternative and safe-haven investment, crude oil as an important commodity or asset, volatility derivatives as a hedging tool, and the flights-to-safety phenomenon (associated with sovereign bonds) as a means of risk-rebalancing which once again has attracted the attention of both researchers and policymakers. However, given our objective to investigate alternative assets' role, we pay particular attention to studies that deal with hedging and diversification strategies. In this context, several scholars such as Tang and Xiong (2012), Silvennoinen and Thorp (2013) and Basher and &Sadorsky (2016) argue that the financialisation of commodities5 markets offers the investors with various approaches to hedge and diversity their portfolios.

On this aspect, Sadorsky (2012) explored the hedging benefits of oil for the European stocks, Raza et al. (2018) investigated the hedging effectiveness of commodities futures for the US real estate stock portfolios, Chang et al. (2010) analyzed hedge abilities of gasoline and oil spot prices against their own future prices in bear and bull markets and Bessler and Wolff (2015) examined the performance of commodities in various assets portfolios. These findings are supported by the correlation between stock prices and natural gas (Kumar et al., 2019).

Narayan and Sharma (2011) reported that oil prices affect U.S firms' returns, and this effect is regime-dependent. By studying the returns and volatility determinants, in their later study, Narayan and Sharma (2014) argued that oil prices are a significant predictor of returns and volatility of stock markets and that the information on commodity futures is helpful to devise trading strategies to gain maximum returns from investment. Similarly, Mensi et al. (2015) reported that commodities' investments are profitable based on trading strategies and that profits are dependent on structural-breaks.

This paper is also associated with another stream of literature on NFTs, and that literature is still growing. Several studies have been conducted after this topic received attention during COVID-19. Dowling (2022a) examined the Decentraland pricing and argues that because of its initial stage of growth, the NFTs market is still inefficient. Karim et al. (2022) investigated the extreme risk transmission of blockchain markets using quantile connectedness methodology and discovered that, among other blockchain markets, NFTs provide greater diversification avenues with significant risk-bearing potential to protect investments and minimize extreme risks. Yousaf and Yarovaya (2022) examined the static and dynamic return and volatility spillovers between DeFi, NFTs, and traditional assets and found some DeFi and NFTs are net transmitters of volatility and return spillovers and connectedness became higher during COVID-19. Another study by Maouchi et al. (2021) discussed digital bubbles in the context of the COVID-19 pandemic, showing specific DeFi and NFT bubbles in summer 2020, with bubbles occurring less frequently before the pandemic period. During the COVID-19 outbreak.

3. Methodology

We used three linear and non-linear GARCH-class models to describe and forecast the volatility of the EGX-30 and Nikkei-225 daily indices return (Abdelhafez, 2018).

3.1Symmetric GARCH Models

3.1.1 The GARCH Model

Linear models are unable to explain characteristics like volatility clustering, leverage effects, leptokurtosis and long memory in financial series (Zivot, 2009). Thus, we employ an econometric method that allows modeling nonlinear patterns as non-constant volatility. Autoregressive conditional heteroscedasticity (ARCH) and its derivative models are popularly utilized in modelling and forecasting asset dynamics. Bollerslev (1986) extended Engle's work (1982) and developed the technique that allows for both autoregressive (AR) and moving average (MA) components in the heteroskedastic variance. This is the generalized Autoregressive Conditional Heteroscedasticity, GARCH (p, q)model. Brooks (2008) suggest that

GARCH (1, 1) model is sufficient to capture the volatility clustering in financial data. In this paper we follow Brooks (2008) suggestion and use GARCH (1, 1) with the following equations:

For a univariate series, let be a mean equation at time t:

$$\boldsymbol{r_t = \mu_t + \varepsilon_t} \quad \textbf{Mean equation} \qquad \textbf{(1)}$$

where: r_t is the return of the asset at time t,

μ_t is conditional mean of r_t, and ε_t is the shock at time t, and:

$$\boldsymbol{\varepsilon_t = \sqrt{\sigma_t e_t}} \quad e_t \sim iid\ N\ (0,1).$$

Then σ_t^2 follows a GARCH (p, q) model if:

$$\boldsymbol{\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2} \quad \textbf{Variance equation} \qquad \textbf{(2)}$$

where: σ_t^2 is conditional variance of r_t, and $\alpha_0 > 0, \alpha_i > 0$, and $\beta_j \geq 0$ conditions.

In order to ensure the stationarity of this model, it must meet the following requirement: the sum of all parameters must be less than one:

$$\sum_{i,j=1}^{max(p,q)} (\alpha_i + \beta_j) < 1.$$

The ARCH (q) model is a special case of the GARCH model $(p, q)$when p =0

α_i and β_j are the coefficient of the parameters ARCH and GARCH, respectively, and ε_{t-i}^2 represents volatility from the previous period, while σ_{t-j}^2represent conditional variance from previous period.

3.2 Asymmetric GARCH Models

Symmetric GARCH models are unable to capture the asymmetry or leverage effects, because the conditional variances σ_t is a function of past values of ε_t^2 and the square function ε_t^2 is symmetric in ε_t. The symmetric GARCH models cannot express the asymmetric effects of negative and positive values for ε_t that can have great impact on market returns (Black 1976). To find out the direction of the volatility or the leverage effect, a variety of asymmetric

GARCH models have been developed such as: GJR-GARCH model and EGARCH model (Dury and Xiao, 2018).

3.2.1 The GJR-GARCH Model

Another model that accounts for asymmetry is GJR-GARCH model proposed by Glosten et al., 1993. The model is a simple extension of standard GARCH, which allows the conditional variance to have a different response to past positive and negative shocks. The model's conditional variance can be written as:

$$\boldsymbol{r_t = \mu_t + \varepsilon_t} \qquad \textbf{Mean equation} \qquad \textbf{(3)}$$

$$\boldsymbol{\varepsilon_{\mathrm{t}} = \sqrt{\sigma_{\mathrm{t}} \mathrm{e}_{\mathrm{t}}}} \quad e_t \sim iid\ N\ (0,1).$$

$$\boldsymbol{\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i\, \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{q} \gamma_i\, \varepsilon_{t-1}^2 d_{t-1}} \ \textbf{Varianceequation} \quad \textbf{(4)}$$

Where $\boldsymbol{\gamma_i}$ is the asymmetric response parameter or leverage parameter and $\boldsymbol{d_{t-1}}$ is defined as:

$$d_{t-1} = \begin{cases} \varepsilon_{\mathrm{t-i}} < 0\ positive\ shocks \\ \varepsilon_{\mathrm{t-i}} \geq 0\ negativeshocks \end{cases}$$

The coefficients at the equation (8) $\gamma > 0$ and $\gamma \neq 0$ show leverage effect and asymmetric shocks respectively. The condition for non-negativity is $\alpha_0 > 0, \alpha_i > 0,$ and $\beta_j \geq 0$ and $(\alpha_i + \gamma_i) \geq 0$.

3.2.2 Multivariate GARCH (MGARCH) Model

MGARCH stands for multivariate GARCH. MGARCH allows the conditional-on-past-history covariance matrix of the dependent variables to follow a flexible dynamic structure (Pilbeam and Langeland, 2015).

4 Data and Empirical Results

4.1 Data

This paper examines the efficiency and asymmetric multiracial features of (EGX30, Oil index), and NFTs (Mana, Tezos), and using Asymmetric

Multiracial Cross-Correlations Analysis covering the period from January 2020 to May 2021.

4.1.1 Descriptive Statistics for Traditional Assets

The data are contained in the Excel file. First, we import the dataset into Stata and tsset Date. Next, to reduce change range and heteroscedasticity, we construct a set of continuously compounded percentage returns called `rEGX30', and `rOil' using the following set of commands, respectively:

generate rEGX30=100*(ln(EGX30/L.EGX30))

generate rOil=100*(ln(Oil/L.Oil))

Figure 1 and figure 2 show the empirical distribution of returns, we use a histogram to illustrate the density of returns. From Figure 1 and figure 2 we see that distribution of returns remarkably differs from normality given the excess kurtosis and light left skewness implying some asymmetry.

Figure 1: The Distribution of Daily Stock Returns for EGX30 from (January 2020 to May 2021)

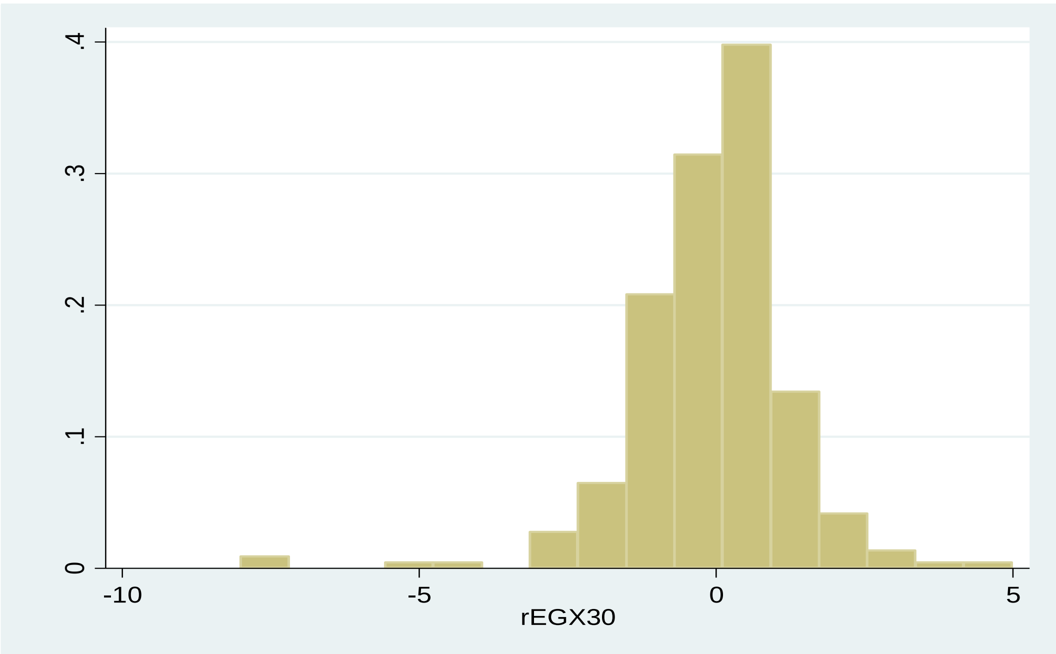

Figure 1: The Distribution of Daily Returns for Oil index from (January 2020 to May 2021)

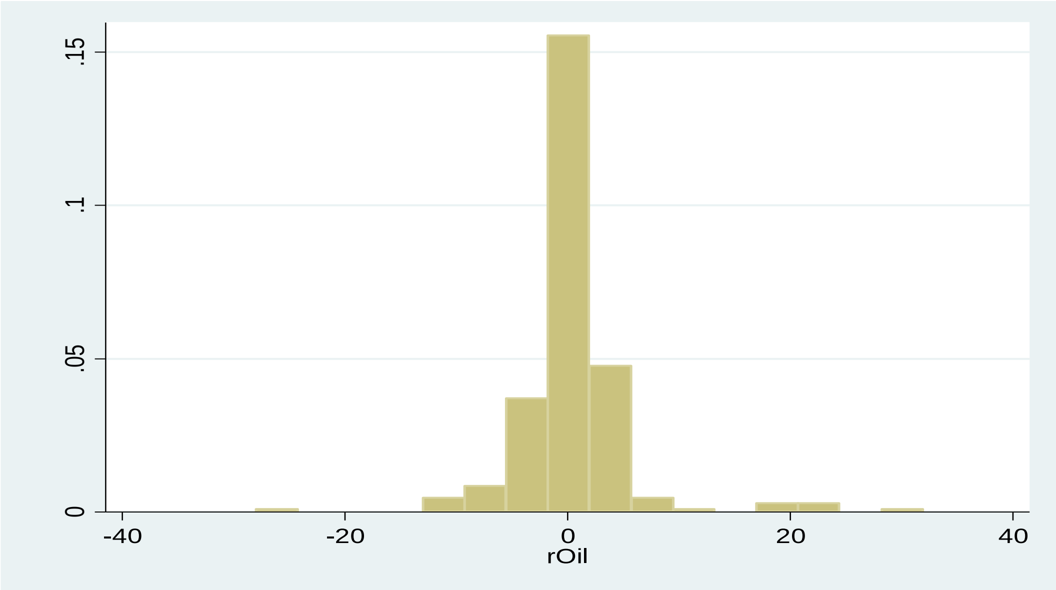

Table 1 and Table 2 present descriptive statistics for the return of EGX30 and Oil. Throughout the sample period, the return of EGX30 and Oil exhibit all positive values during the sample period, from which lower mean value of -0.06 is found for Egypt, compared to higher mean value of 0.4 is found for Oil.

As shown in Table 1 and Table 2, statistics for skewness and kurtosis, all confirm that price distributions for the return of EGX30 and Oil are not normally distributed. The distribution of returns remarkably differs from normality given the excess kurtosis and light left skewness implying some asymmetry. Heavy tailed leptokurtic distribution implies the index has higher risk and return in the sample space. Leptokurtic distributions can also show a higher value at risk in the left tail due to the larger amount of value under the curve in the worst-case scenarios. Overall, a greater probability for negative returns farther from the mean on the left side of the distribution leads to a higher value at risk.

Besides these, financial assets returns are observed to often have thicker tails than expected under normality. Some studies propose that these tails might be so thick as to have come from a Cauchy distribution, or other distributions with infinite moments (Mandelbrot, 1963). Values of the standard deviations obtained for Oil is the highest, i.e., 4.9, implying that this market is the most volatile market compared with Egypt stock market.

Table 1: Descriptive Statistics of the Stock Returns for EGX30

	Percentiles	Smallest		
1%	-4.952085	-8.005665		
5%	-1.868866	-7.362751		
10%	-1.354658	-4.952085	Obs	266
25%	-.7461069	-4.600555	Sum of Wgt.	266
50%	.054012		**Mean**	**-.0652482**
		Largest	**Std.Dev.**	**1.353399**
75%	.6168773	3.006141		
90%	1.183063	3.210531	Variance	1.831688
95%	1.848107	4.088056	**Skewness**	**-1.271286**
99%	3.210531	4.987894	**Kurtosis**	**11.09465**

Table 2: Descriptive Statistics of the Returns for Oil

	Percentiles	Smallest		
1%	-10.82901	-27.99201		
5%	-5.845281	-11.7238		
10%	-3.451685	-10.82901	Obs	280
25%	-1.151304	-10.6087	Sum of Wgt.	280
50%	.2527793		**Mean**	**.412311**
			Std.Dev.	**4.911352**
75%	1.809761	21.35741		
90%	3.464247	22.04812	Variance	24.12137
95%	5.354204	22.394	**Skewness**	**1.470551**
99%	22.04812	31.96337	**Kurtosis**	**17.18479**

4.1.2 Descriptive Statistics for NFTs

The data are contained in the Excel file. First, we import the dataset into Stata and tsset Date. Next, to reduce change range and heteroscedasticity, we construct a set of continuously compounded percentage returns called `rMana', and `rTezos' using the following set of commands, respectively:

generate rMANA=100*(ln(MANA/L.MANA))

generate rTEZOS=100*(ln(TEZOS/L.TEZOS))

Figure 3 and figure 4 show the empirical distribution of returns, we use a histogram to illustrate the density of returns. From Figure 3 and figure 4 we see that distribution of returns remarkably differs from normality given the excess kurtosis and light left skewness implying some asymmetry.

Figure 3: The Distribution of Daily Stock Returns for Mana from (January 2020 to May 2021)

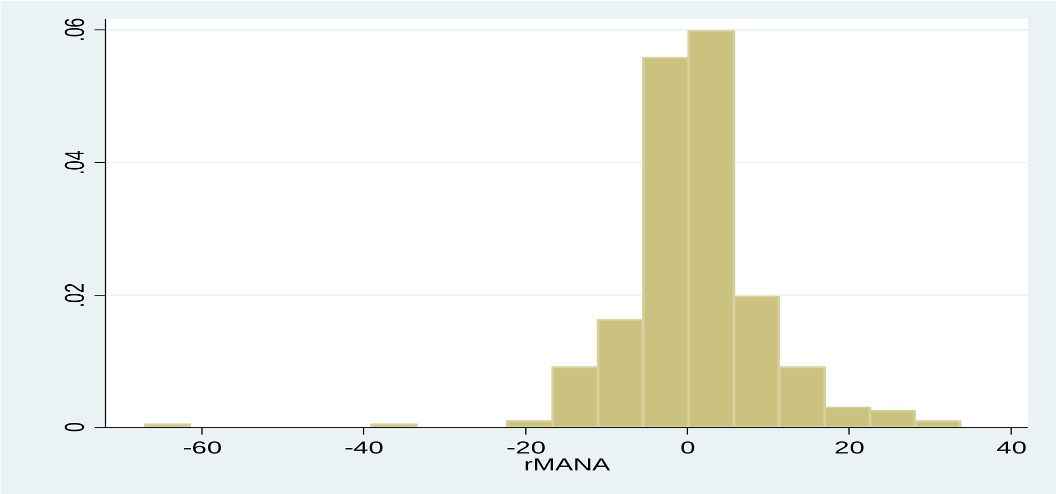

Figure 4: The Distribution of Daily Stock Returns for Tezos from (January 2020 to May 2021)

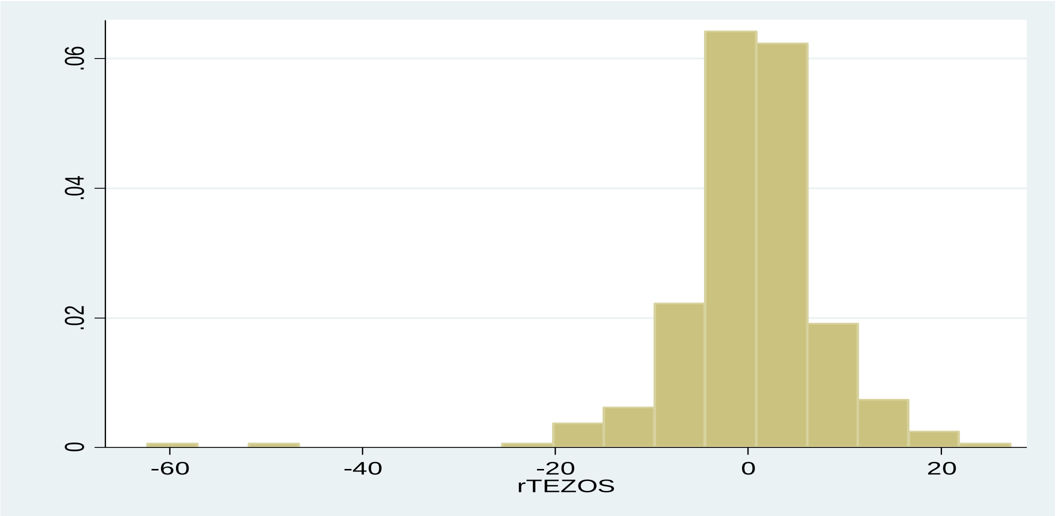

Table 3 and Table 4 present descriptive statistics for the return of Mana and Tezos. Throughout the sample period, the return of Mana and Tezos exhibit all positive values during the sample period, from which higher mean value of.8 is found for Mana, compared to lower mean value of .32 is found for Tezos.

As shown in Table 3 and Table 4, statistics for skewness and kurtosis, all confirm that price distributions for the return of Mana and Tezos are not normally distributed. The distribution of returns remarkably differs from normality given the excess kurtosis and light left skewness implying some asymmetry. Heavy tailed leptokurtic distribution implies the index has higher risk and return in the sample space. Leptokurtic distributions can also show a higher value at risk in the left tail due to the larger amount of value under the curve in the worst-case scenarios. Overall, a greater probability for negative returns farther from the mean on the left side of the distribution leads to a higher value at risk.

Besides these, financial assets returns are observed to often have thicker tails than expected under normality. Some studies propose that these tails might be so thick as to have come from a Cauchy distribution, or other distributions with infinite moments (Mandelbrot, 1963). Values of the standard deviations obtained for Mana is the highest, i.e., 8.6, implying that this market is the most volatile market compared with Tezos.

Table 3: Descriptive Statistics of the Returns for Mana

	Percentiles	Smallest		
1%	-17.30622	-67.05473		
5%	-11.85265	-37.86285		
10%	-7.223165	-20.34385	Obs	352
25%	-2.87823	-17.30622	Sum of Wgt.	352
50%	.5203059		**Mean**	**.8586154**
		Largest	**Std.Dev.**	**8.66507**
75%	4.777193	25.50319		
90%	9.720672	26.39655	Variance	75.08344
95%	15.14259	29.94766	**Skewness**	**-1.033898**
99%	25.50319	33.75539	**Kurtosis**	**15.06297**

Table 4: Descriptive Statistics of the Returns for Tezos

	Percentiles	Smallest		
1%	-19.22706	-62.31122		
5%	-11.58982	-46.76905		
10%	-6.514585	-20.98329	Obs	308
25%	-3.118873	-19.22706	Sum of Wgt.	308
50%	.4596619		**Mean**	**.3264657**
		Largest	**Std.Dev.**	**8.001775**
75%	3.933252	17.5597		
90%	8.685456	19.51268	Variance	64.02841
95%	12.9148	19.82927	**Skewness**	**-2.093356**
99%	17.5597	27.15237	**Kurtosis**	**18.41052**

4.2 Models Tests

4.2.1 Testing for Serial Correlation for Traditional Assets

Durbin-Watson Test is one of the tests that reveal the existence of a serial correlation of the first degree (for one period). Durbin–Watson d statistic (Durbin and Watson 1950) tests for first-order serial correlation in the disturbance when all the regressors are strictly exogenous (Brooks, 2008). If we are not willing to assume that all the regressors is strictly exogenous, we could instead use Durbin's alternative test or the Breusch–Godfrey to test for first-order serial correlation. Following this procedure, we first regress return series (regress rEGX30, regress rOil) on its mean and obtain residuals. We then test the null hypothesis that there is no first-order serial correlation. Therefore, for reEGX30, and rOil table3, and table 4 respectively indicates that the test strongly accepts the null of no first-order serial correlation.

Table 5: Durbin's Alternative Test for Autocorrelation for Stock Returns for EGX30

lags(p)	chi2	Df	Prob>chi2
1	0.630	1	0.4273

H0: no serial correlation

Table 6: Durbin's Alternative Test for Autocorrelation for Returns for Oil

lags(p)	chi2	Df	Prob>chi2
1	1.873	1	0.1711

H0: no serial correlation

4.2.2 Testing for Serial Correlation for NFTs

Durbin-Watson Test is one of the tests that reveal the existence of a serial correlation of the first degree (for one period). Durbin–Watson d statistic (Durbin and Watson 1950) tests for first-order serial correlation in the disturbance when all the regressors are strictly exogenous (Brooks, 2008). If we are not willing to assume that all the regressors is strictly exogenous, we could instead use Durbin's alternative test or the Breusch–Godfrey to test for first-order serial correlation. Following this procedure, we first regress return series (regress rMana, regress rTezos) on its mean and obtain residuals. We then test the null hypothesis that there is no first-order serial correlation. The test strongly rejects the null of no first-order serial correlation, so we decide to refit the model with three lags of rMana, and rTezos included as regressors and then rerun estat durbinalt.

The output from estat durbinalt indicates that including the three lags of rMana, and rTezos has removed any serial correlation from the errors as shown in Table 7, and Table 8 and the test strongly accepts the null of no first-order serial correlation.

Table 7: Durbin's Alternative Test for Autocorrelation for Returns for Mana

lags(p)	chi2	Df	Prob>chi2
1	1.019	1	0.3128
2	1.019	1	0.3128
3	1.019	1	0.3128

H0: no serial correlation

Table 8: Durbin's Alternative Test for Autocorrelation for Returns for Tezos

lags(p)	chi2	Df	Prob>chi2
1	.967	1	0.3253
2	.967	1	0.3253
3	.967	1	0.3253

H0: no serial correlation

4.2.3 Testing for Autoregressive Conditional Heteroskedasticity for Traditional Assets

Engle (1982) suggests a Lagrange Multiplier Test (LM) for checking for autoregressive conditional heteroskedasticity (ARCH) in the errors. Following this procedure, we first regress return series (regress rEGX30, regress rOil) on its mean and obtain residuals. We then test the null hypothesis that there are no ARCH effects in the residuals. The results of this ARCH-LM test for EGX30 series and Oil series are reported in Table 9 and Table 10, respectively. Additionally, the volatility clustering pattern observed on return series graph depicted on Figure 1 and Figure 2 above suggests ARCH type model, as well.

Table 9 shows the results for tests of ARCH(1), ARCH(2), and ARCH(3) effects for EGX30 series, respectively. At the 1% significance level, all three tests reject the null hypothesis that the errors are not autoregressive conditional heteroskedastic. Table 10 shows the results for tests of ARCH(1), ARCH(2), and ARCH(3) effects for Oil series, respectively. At the 1% significance level, all three tests reject the null hypothesis that the errors are not autoregressive conditional heteroskedastic.

Table 9: LM Test for Autoregressive Conditional Heteroskedasticity (ARCH) for Stock Returns for EGX30

lags(p)	chi2	Df	Prob>chi2
1	20.725	1	0.0000
2	62.000	2	0.0000
3	50.389	3	0.0000

H0: no ARCH effects vs. H1: ARCH(p) disturbance

Table 10: LM Test for Autoregressive Conditional Heteroskedasticity (ARCH) for Returns for Oil

lags(p)	chi2	Df	Prob>chi2
1	43.453	1	0.0000
2	55.791	2	0.0000
3	28.170	3	0.0000

H0: no ARCH effects vs. H1: ARCH(p) disturbance

Therefore, these results reject *H0* and show that the series has ARCH effect on the residuals, implying that variance of returns of EGX30 series and Oil series are non-constant.

4.2.4 Testing for Autoregressive Conditional Heteroskedasticity for NFTs

Engle (1982) suggests a Lagrange Multiplier Test (LM) for checking for autoregressive conditional heteroskedasticity (ARCH) in the errors. Following this procedure, we first regress return series (regress rMana, regress rTezo) on its mean and obtain residuals. We then test the null hypothesis that there are no ARCH effects in the residuals. The results of this ARCH-LM test for Mana series and Tezos series are reported in Table 11and Table 12, respectively. Additionally, the volatility clustering pattern observed on return series graph depicted on Figure 1 and Figure 2 above suggests ARCH type model, as well.

Table 11 shows the results for tests of ARCH(1) effect for Mana series. At the 1% significance level, the test rejects the null hypothesis that the error is not autoregressive conditional heteroskedastic. Table 12 shows the results for tests of ARCH(1) effect for Tezos series. At the 1% significance level, the test rejects the null hypothesis that the error is not autoregressive conditional heteroskedastic.

Table 11: LM Test for Autoregressive Conditional Heteroskedasticity (ARCH) for Returns for Mana

lags(p)	chi2	Df	Prob>chi2
1	4.490	1	0.0341

H0: no ARCH effects vs. H1: ARCH(p) disturbance

Table 12: LM Test for Autoregressive Conditional Heteroskedasticity (ARCH) for Returns for Tezos

lags(p)	chi2	Df	Prob>chi2
1	5.146	1	0.0233

H0: no ARCH effects vs. H1: ARCH(p) disturbance

Therefore, these results reject *H0* and show that the series has ARCH effect on the residuals, implying that variance of returns of Mana series and Tezos series are non-constant.

4.3 Empirical Results

Since the residuals have ARCH effects we employ GARCH process to model this conditional heteroscedasticity. Considering that the data is not normally distributed we estimate GARCH parameters and obtain ARMA(1,1) mean equation.

4.3.1 Parameter Estimation of Symmetric GARCH Models

1. **The GARCH (1, 1) Model**

The reported α_1 (ARCH term) measures the extent to which a volatility shock today feeds through into next period's volatility (Campbell et al. 1997). For our series, EGX30, this coefficient is 0.699096 and this shows the presence of volatility clustering in the series over the period. The volatility changes over time and its degree shows a tendency to persist, i.e., there are periods of low volatility and periods where volatility is high. The estimate of β_1 (GARCH term) coefficient is 0.2738783 indicates a long memory in the variance. This means that changes in the current volatility will affect future volatilities for a long period or the impact of old news on volatility is long lasting. The sum of ARCH and GARCH terms $\alpha_1 + \beta_1$ is 0.9729743 indicating volatility shocks are quite persistent. The financial implication of these coefficients for investors is that EGX30 index returns' volatility exhibits clustering, and this permits investors to establish future positions in expectation of this characteristic**.** The same is for our series, Oil, the estimate of α_1 coefficient is 0.534525 and this shows the presence of volatility clustering in the series over the period. The volatility changes over time and its degree shows a tendency to persist, i.e., there are periods of low volatility and periods where volatility is high. The estimate of β1 (GARCH term) coefficient is 0.599726 indicates a long memory in the variance. The sum of ARCH and GARCH terms $\alpha_1 + \beta_1$is 1.1314251 indicate that the random error series is non-stationary, and this is the main difference between the estimation results of EGX30 and Oil indices. Estimation results are reported on Table 13 and Table 14.

It is clear that the parameters of the model are significant, but the estimated parameter β1 (GARCH term**)** has a positive sign but is statistically not significant for stock returns for EGX30. The individual conditional variance coefficients are also as one would expect. The variance intercept term cons in the `ARCH'-parameter **`L1.arch'** is around 0.69, 0.53 while the coefficient on the lagged conditional variance **`L1.garch'** is around 0. 27, 0.59 for EGX30 and Oil indices.

Table 13: Estimation Results of GARCH Model for Stock Returns for EGX30

Number of obs = 280

Distribution: Gaussian

Log likelihood = -430.6426

	rEGX30	Coef.	Std.Err.	z	P>|z|	[95% Conf.Interval]	
rEGX30	_cons	0.014297	0.068536	0.21	0.835	-0.12003	0.148625
ARCH	Arch L1.	**0.699096**	0.096525	7.24	**0.000**	0.509912	0.888281
	Garch L1.	**0.273878**	0.169104	1.62	**0.105**	-0.05756	0.605317
	_cons	0.262747	0.246842	1.06	0.287	-0.22105	0.746548

Table 14: Estimation Results of GARCH Model for Returns for Oil

Number of obs =
280
Distribution: Gaussian
Log likelihood = -
796.6187

	rOil	Coef.	Std.Err.	z	P>|z|	[95% Conf.Interval]	
rOil	_cons	0.301804	0.226705	1.33	0.183	-0.14253	0.746138
ARCH	arch L1.	**0.534525**	0.059892	8.92	**0.000**	0.417139	0.65191
	garch L1.	**0.599726**	0.085054	7.05	**0.000**	0.433023	0.766429
	_cons	-0.62227	1.588294	-0.39	0.695	-3.73527	2.490726

4.3.2Parameter Estimation of Asymmetric GARCH Models

1. The GJR-GARCH (1, 1) Model

The GJR model is a simple extension of the GARCH model with an additional term added to account for possible asymmetries. It should be noted that the GARCH model is a special case of the GJR model. If we put $\boldsymbol{\gamma}_{\boldsymbol{j}} = 0$ in the GJR model, which means no asymmetric effects exist, we obtain the GARCH model. It is clear that the parameters of the model are significant for EGX 30 and Oil indices, and this indicates that the model is appropriate. But the estimated parameter β1 (GARCH term**)** has a positive sign but is statistically not significant for stock returns for EGX30, and a negative sign but is statistically not significant for stock returns for Oil .

We find a negative coefficient estimate on the “**L1.tarch”** term (leverage asymmetric effect) for Oil index, which is not what we would expect to find according to the leverage expect explanation if we were modelling return volatilities. This is significant and this means that the volatility is asymmetry. The negative L1.tarch coefficient implies that negative effects (such as information on price declines) lead in the coming period to greater conditional variance than positive effects, leading to further price declines. This indicates that the existence of leverage effect is observed in returns of the Oil index. Estimation results are reported on Table 15 and Table 16.

Table 15: Estimation Results of GJR-GARCH Model for Stock Returns for EGX30

Number of obs = 266

Distribution: Gaussian

Log likelihood = -428.5548

	rEGX30	Coef.	Std.Err.	z	P>|z|	[95% Conf.Interval]	
rEGX30	|						
	_cons	0.03976	0.072418	0.55	0.583	-0.10218	0.181697
ARCH	|						
	arch						
	L1.	0.371026	0.174344	2.13	**0.033**	0.029319	0.712734
	|						
	tarch						
	L1.	0.478131	0.167368	2.86	**0.004**	0.150096	0.806166
	|						
	garch						
	L1.	0.249903	0.145683	1.72	**0.086**	-0.03563	0.535435
	|						
	_cons	0.314404	0.221145	1.42	0.155	-0.11903	0.74784

Table 16: Estimation Results of GJR-GARCH Model for Stock Returns for Oil

Number of obs = 280

Distribution: Gaussian

Log likelihood = -786.6443

	rOil	Coef.	Std.Err.	z	P>|z|	[95% Conf.Interval]	
rOil	_cons	0.312269	0.132104	2.36	0.018	0.053349	0.571188
ARCH	arch L1.	2.385637	0.52686	4.53	**0.000**	1.353011	3.418262
	tarch L1.	-1.68461	0.515891	-3.27	**0.001**	-2.69574	-0.67348
	garch L1.	-0.04336	0.02882	-1.5	**0.132**	-0.09985	0.013127
	_cons	7.768165	0.783714	9.91	0	6.232114	9.304215

4.3.3 Parameter Estimation of Multivariate GARCH Models

Multivariate GARCH models are in spirit very similar to their univariate counterparts, except that the former also specify equations for how the covariances move over time and are therefore by their nature inherently more complex to specify and estimate. For each dependent variable, we first find the estimates for the conditional mean equation, followed by the conditional variance estimates in a separate panel. It is evident that the parameter estimates are all both plausible and statistically significant. In the final panels Stata reports results for the conditional correlation parameters. For example, the conditional correlation between the standardized residuals for corr (rOil, rTEZOS) estimated to be 0.1590806 and statistically significant, and the conditional correlation between the standardized residuals for corr (rTEZOS, rMANA) estimated to be 0.6580539 and statistically significant.

Table 17: Estimation Results of Multivariate GARCH Models for EGX30, Oil, Mana, and Tezos

Number of obs = 173

Distribution: Gaussian

Log likelihood = -1895.276

		Coef.	Std.Err.	z	P>|z|	[95% Conf.Interval]	
rOil							
	_cons	0.920888	0.253029	3.64	0.000	0.424959	1.416816
ARCH_rOil							
	arch						
	L1.	0.947792	0.220355	4.3	0.000	0.515905	1.37968
	garch						
	L1.	-0.05735	0.017584	-3.26	0.001	-0.09181	-0.02289
	_cons	11.87615	2.296705	5.17	0.000	7.374694	16.37761
rEGX30							
	_cons	0.079527	0.07622	1.04	0.297	-0.06986	0.228916
ARCH_rEGX30							
	arch						
	L1.	0.460495	0.208682	2.21	0.027	0.051486	0.869504
	garch						
	L1.	0.288709	0.66803	0.43	0.666	-1.02061	1.598023
	_cons	0.307589	0.760024	0.4	0.686	-1.18203	1.797209
rTEZOS							
	_cons	-0.54714	0.468867	-1.17	0.243	-1.4661	0.371824
ARCH_rTEZOS							
	arch						
	L1.	0.32652	0.108809	3	0.003	0.113259	0.539781

	garch L1.	0.08962	0.36384	0.25	0.805	-0.62349	0.802732
	_cons	28.63437	15.98638	1.79	0.073	-2.69836	59.9671
rMANA	_cons	0.118351	0.572891	0.21	0.836	-1.0045	1.241197
ARCH_rMANA	arch L1.	0.220212	0.114073	1.93	0.054	-0.00337	0.443791
	garch L1.	0.649579	1.250351	0.52	0.603	-1.80106	3.100222
	_cons	10.382	74.27754	0.14	0.889	-135.199	155.9633
	corr(rOil,rEGX30)|	0.119407	0.076273	1.57	0.117	-0.03008	0.268899
	corr(rOil,rTEZOS)|	0.159081	0.075401	2.11	**0.035**	0.011297	0.306864
	corr(rOil,rMANA)|	0.137407	0.076062	1.81	0.071	-0.01167	0.286486
	corr(rEGX30,rTEZOS)|	0.017624	0.077009	0.23	0.819	-0.13331	0.168558
	corr(rEGX30,rMANA)|	0.053387	0.076922	0.69	0.488	-0.09738	0.204151
	corr(rTEZOS,rMANA)|	0.658054	0.044032	14.94	**0.000**	0.571752	0.744355

4.3.4 Choosing the Best Fitting Model

To evaluate the performance of the GARCH models used to analyze the EGX30 and Oil indices data, we use the following selection criteria:

1. Akaike Information Criterion (AIC).
2. Bayesian information criterion (BIC).

Table 18: Results of Different GARCH Models Tests for EGX30

Model	**AIC**	**BIC**
GARCH	869.2852	883.6192
GJR-GARCH	**867.1097**	**885.0271**
Multivariate GARCH	1787.288	1816.928

Table 19: Results of Different GARCH Models Tests for Oil

Model	AIC	BIC
GARCH	1601.237	1615.776
GJR-GARCH	**1583.289**	**1601.463**
Multivariate GARCH	1787.288	1816.928

From Table (18, 19) above, it is clear that the GJR-GARCH model has the lowest AIC and BIC values (867.1097, 885.0271, 1583.289, 1601.463) for EGX30 and Oil indices respectively. Thus, we can conclude that **GJR-GARCH** model is the best model for the EGX30 and Oil indices.

5. Conclusion

This paper uses standard GARCH, asymmetric GJR-GARCH models to analyze volatility in Traditional Assets (EGX30, Oil), and NFTs (Mana, and Tezos) returns for the period of January 2020 to May 2021. Our purpose was to evaluate the forecasting performance of linear and non-linear (GARCH)-class models, these models are capable of capturing symmetric and asymmetric dynamics such as leptokurtosis, volatility clustering, and leverage effects of the return series.

The results show that EGX30 and Oil indices returns deviate from normality and exhibit volatility clustering with varying variance in the residuals, and this permits investors to establish future positions in expectation of this characteristic. These findings show nonlinear structure in the conditional variance of the returns and this dynamic may be simulated with the GARCH (1, 1) model. Estimates of the model $(\alpha_1 + \beta_1)$ for EGX30 show the variance of the series has long memory and shocks on volatility are quite persistent, and this support the mean reverting process. The sum of ARCH and GARCH terms for Oil indicate that the random error series is non-stationary

The findings of GJR-GARCH model show that the series have leverage effect, and the impact of the shocks is asymmetric, and that means the impact of negative shocks on volatility are higher than positive shocks of the same size for both EGX30 and Oil indices. This finding is consistent with the literature. Multivariate GARCH model indicates a significant positive relationship between rOil, and rTEZOS. Additionally, Multivariate GARCH model indicates a significant positive relationship between rTEZOS, and rMANA.

We compared the forecasting performance of several GARCH models in regard to in and out-of-sample forecast ability. The GARCH models were evaluated based on their ability to forecast future returns. According to the results obtained by the two selection criteria —AIC, and BIC—we concluded that the most appropriate models for modeling the volatility of EGX30 and Oil imdices for the full sample is **GJR-GARCH** model. Furthermore, the results of this study support those of previous studies (Abdalla and Winker, 2012; Abdelhafez, 2018), in which it is concluded that compared with linear GARCH-class models, non-linear GARCH-class models are a better fit for measuring the volatility of stock market returns (e.g., Gabriel and Ugochukwu, 2012; Al Rahahleh and Bhatti, 2017). Therefore, our results are of benefit to policy-makers in predicting the efficiency and asymmetric multiracial features of NFTs (Mana, Tezos), and traditional assets (EGX30, Oil index) using Asymmetric Multiracial Cross-Correlations Analysis.

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ملخص:

هذا البحث يقوم بدراسة كفاءة و خصائص الأصول المالية غير التقليدية و الأصول المالية التقليدية باستخدام نماذج .MGARCH في الفترة من يناير 2020 الى مايو2021 مع الأخذ في الاعتبار الاختلافات الجوهرية بين الأصول المالية. وتم التوصل الى توليفات الأصول المالية التقليدية و الأصول المالية الغيرتقليدية الأكثر فعالية من خلال استخدام النماذج السابقة الذكر لقياس التقلبات السعرية.

الكلمات الدالة

التقلبات، NFTs، الأصول المالية التقليدية، وMGARCH