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COVID-19 PANDEMIC AND FINANCIAL MARKET VOLATILITY; EVIDENCE FROM GARCH MODELS

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Abstract
This study investigates the impact of the COVID-19 pandemic on financial market volatility using daily time series data of Bitcoin, the EUR, the S&P 500, Gold, Crude Oil, and Sugar from November 2018 to May 2023. The primary objective is to analyse volatility dynamics and identify the most suitable model for capturing these trends. Utilising GARCH (1, 1), GJR-GARCH (1, 1), and EGARCH (1, 1) models, this study examines the persistence, asymmetry, and influence of pandemic-related shocks on market volatility. The findings reveal high volatility persistence across financial markets, with significant positive asymmetric behaviour observed in Crude Oil and the S&P 500 index. EGARCH emerged as the most effective model for pre-pandemic volatility, while all GARCH models captured pandemic-induced volatilities effectively. The study concludes that the COVID-19 pandemic amplified financial market turbulence, emphasising the need for robust risk management strategies. Policymakers and investors are advised to prioritise portfolio diversification and leverage advanced econometric models to effectively navigate crises. The recommendations include integrating dynamic risk management frameworks and stress-testing mechanisms to enhance market resilience. This research contributes to the growing body of knowledge on the interplay between global crises and financial market behaviour, offering valuable insights for mitigating future uncertainties.

1. Introduction

The emergence of the COVID-19 pandemic in late 2019, precipitated by the novel coronavirus SARS-CoV-2, instigated a seismic upheaval across global economies. The contagion swiftly evolved into a formidable health crisis, unfurling unprecedented disruptions across various economic sectors (Maital and Barzani, 2020). One of the most pronounced impacts of this pandemic was witnessed in financial markets, where uncertainty and fear

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proliferated rapidly, triggering extreme volatility (McKibbin and Fernando, 2020). In response to the outbreak, nations worldwide swiftly implemented stringent policies, including travel restrictions and quarantine measures, alongside the cancellation of cultural and sporting events (Ozili and Arun, 2020). These actions, while essential for public health, substantially curtailed economic activities on a global scale, contributing to a climate of heightened uncertainty (Amankwah-Amoah et al., 2021).

Empirical studies have underscored the profound and lasting repercussions of the COVID-19 pandemic on economies, characterised by an elevated risk of business failures and surging unemployment rates (Holder et al., 2021). Financial markets, in particular, experienced heightened volatility and interconnectedness, intensified by speculative trading activities by international investors (Montenovo et al., 2020). The resulting speculative bubble and subsequent crashes inflicted significant losses on investors worldwide, amplifying the prevailing economic turmoil (Aslam et al., 2020b).

Moreover, the pandemic engendered a pervasive sense of fear and risk among investors, altering their behaviour and worsening market volatility (Zhang and Hamori, 2021). Studies have demonstrated the pandemic's deleterious effects on various financial markets, with stock markets bearing the brunt of the downturn (Alfaro et al., 2020). Companies across different sectors, particularly those in China and the United States, experienced substantial declines in stock returns attributable to COVID-19 (Al-Awadhi et al., 2020).

The adverse impact of the pandemic reverberated across international equity markets, with countries like Singapore, Japan, and Korea witnessing significant downturns in equity values (Zhang et al., 2020). Furthermore, empirical analyses utilising GARCH family models have shed light on the dynamics of market volatility during the pandemic, highlighting its persistence and asymmetry in response to negative shocks (He et al., 2020).

Volatility, a critical parameter in financial models, assumes heightened significance during periods of market uncertainty, such as the COVID-19 pandemic (Budiarso et al., 2020). The magnitude of volatility reflects the degree of uncertainty surrounding asset price fluctuations, with higher volatility signaling increased market turbulence and vice versa (Ortmann et al., 2020). Notably, financial time series data exhibit distinct characteristics necessitating sophisticated modelling approaches, such as GARCH models, to capture the evolving volatility patterns accurately (Rastogi, 2014).

The GARCH family of models, comprising GARCH (1, 1), GJR-GARCH (1, 1), and EGARCH (1, 1), has emerged as the gold standard for modelling financial market volatility (Brooks and Rew, 2002). These models offer nuanced insights into volatility dynamics, considering factors like asymmetric responses to shocks and persistence of volatility clusters (Aslam et al., 2022). However, the existing literature on market volatility during the COVID-19 pandemic remains limited, warranting further investigation into the efficacy of GARCH models in capturing evolving volatility patterns across different financial markets.

Hence, this study aims to fill this gap by analysing the volatility of six major financial markets—Bitcoin, EUR, S&P 500, Gold, Crude Oil, and Sugar—during the COVID-19 pandemic using GARCH family models. By applying these models, the study seeks to identify the most suitable model for capturing market volatility and assess the impact of the pandemic on volatility dynamics across the selected financial assets.

Through a comprehensive analysis of market volatility and its determinants during the pandemic, this study endeavours to provide valuable insights for investors and policymakers navigating the tumultuous financial landscape precipitated by COVID-19 (Kodres, 2020). Ultimately, a deeper understanding of the interplay between the pandemic and financial market volatility is crucial for devising effective risk management strategies and informed investment decisions in an increasingly uncertain global environment.

2. GARCH Models

GARCH models, or Generalised Autoregressive Conditional Heteroskedasticity models, are widely used in financial econometrics to model and forecast time-varying volatility in financial returns. Engle (1982) introduced the concept of autoregressive conditional heteroskedasticity (ARCH) to capture the clustering of volatility in financial time series data. ARCH models allow the conditional variance of a financial asset's returns to be modelled as a function of past squared returns. Bollerslev (1986) extended the ARCH framework to the Generalised Autoregressive Conditional Heteroskedasticity (GARCH) model, which incorporates the lagged values of both returns and conditional variances in the volatility equation.

The GARCH (1, 1) model, proposed by Bollerslev (1986), is one of the most commonly used specifications in the GARCH family of models. It models the conditional variance of returns as a linear combination of lagged squared returns and lagged conditional variances. The GARCH (1, 1) model allows for asymmetry in the response of volatility to positive and negative shocks, capturing the phenomenon of volatility clustering observed in financial time series data.

In addition to the standard GARCH (1, 1) model, several extensions have been proposed to capture specific features of financial market data. The GJR-GARCH (1, 1) model, introduced by Glosten, Jagannathan, and Runkle (1993), adds an additional parameter to the GARCH model to capture the asymmetry in the response of volatility to negative shocks. This allows for a more flexible modelling of the volatility process, particularly during periods of market stress.

Another widely used extension of the GARCH model is the Exponential GARCH (EGARCH) model, introduced by Nelson (1991). The EGARCH (1, 1) model allows the conditional variance to be modelled as a nonlinear function of past returns, capturing the asymmetric response of volatility to positive and negative shocks. Unlike the GARCH model, the EGARCH model allows for the possibility of leverage effects, where negative shocks have a larger impact on volatility than positive shocks of the same magnitude.

Mathematically, the GARCH (1, 1) model can be expressed as

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \mu_t^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}{}^2$$

The GJR-GARCH (1, 1) model extends the GARCH (1, 1) model by introducing an additional parameter γγ to capture the asymmetry in the response of volatility to negative shocks:

$$\sigma_t^2 = \omega + \alpha_1 \mu^2{}_{t-1} + \beta_i \sigma_{t-1}{}^2 + \gamma_i I_{t-1} \mu_{t-1}{}^2$$

The EGARCH (1, 1) model can be expressed as

$$\log h_t = (\omega - 1) + \alpha / \eta_{t-1} / + \gamma \eta_{t-1} + \beta \log h_{t-1}$$

These models provide a framework for analysing and forecasting the dynamics of volatility in financial markets, allowing investors and policymakers to better understand and manage risk in their investment decisions.

Nelson (1991) introduced the Exponential GARCH (EGARCH) model as an extension of the GARCH framework to address some limitations, particularly in capturing the asymmetric response of volatility to shocks. The EGARCH model allows the conditional variance to be expressed as a nonlinear function of past returns, enabling it to capture asymmetries more effectively than the standard GARCH model. This nonlinearity is achieved by taking the logarithm of the conditional variance, which relaxes the positive constraints among the model parameters.

The EGARCH model's ability to capture volatility persistence shocks makes it particularly suitable for modelling financial time series data during periods of extreme market conditions, such as the COVID-19 pandemic. During such periods, the financial markets experience heightened uncertainty and variability, leading to increased risk and fluctuations in returns. The EGARCH model's flexibility in capturing asymmetric responses to shocks allows it to provide more accurate forecasts of volatility under such conditions.

3. Research Design

The research design will entail investigating the impact of the COVID-19 pandemic on market volatility and asymmetric behaviour across Bitcoin, the EUR, the S&P 500 index, Gold, Crude Oil, and Sugar. Utilising GARCH (1, 1), GJR-GARCH (1, 1), and EGARCH (1, 1) econometric models, daily time series returns data from 2018, to 2021, will be analysed. The design aims to systematically examine the persistence of volatility in financial markets during the pandemic period, particularly focusing on the observed positive asymmetric behaviour in Crude Oil and the S&P 500 index. Moreover, it will seek to evaluate the suitability of the EGARCH model in capturing pre-pandemic volatilities compared to other GARCH variants.

4. Technique for Data Analysis

The technique employed in this study involves the utilisation of GARCH models to analyse the impact of the COVID-19 pandemic on financial market volatility. The GARCH (Generalised Autoregressive Conditional Heteroskedasticity) model, introduced by Bollerslev in 1986, is used to model the volatility of financial time series. Specifically, the GARCH (1, 1) model is recommended to model the conditional volatility of market returns. This model is represented as

$$GARCH(1,1): \sigma_t^{\,2} = \omega + \alpha\varepsilon^2_{t-1} + \beta\sigma^2_{t-1}$$ where;

$\sigma t2$ is the conditional variance at time t.

ω is the constant term.

α is the coefficient of the lagged squared error term

β is the coefficient of the lagged conditional variance

ε is the squared error term times

This model allows capturing dynamic volatility phenomena and clustering in financial returns volatility, which is essential for understanding the impact of the COVID-19 pandemic on financial markets.

The EGARCH (Exponential Generalised Autoregressive Conditional Heteroskedasticity) model is indeed an extension of the traditional GARCH model. It is designed to capture the asymmetry often observed in financial time series data, where volatility tends to respond differently to positive and negative shocks.

The EGARCH (1,1) model equation can be expressed as

$$Log(\sigma_t^{\,2}) = \omega + \alpha\left(\frac{|r_{t-1}|}{\sigma_{t-1}}\right) + \beta\log(\sigma^2_{t-1}) + \gamma r_{t-1}$$

Where;

$\sigma_t^{\,2}$ is the conditional variance at time t

r_{t-1} is the return at time t-1

ω, α, β *and* γ *are the parameters estimated from the data*

The additional term γr_{t-1} captures the leverage effect, where negative returns tend to have a larger impact on volatility than positive returns of the same magnitude. This reflects investors' asymmetric reactions to positive and negative news.

By incorporating this asymmetry, the EGARCH model provides a more flexible framework for modelling financial time series data, allowing it to better capture the complex dynamics of volatility.

Moreover, the GJR-GARCH model, standing for Generalised Autoregressive Conditional Heteroskedasticity model with Glosten, Jagannathan, and Runkle extensions, is widely employed in financial analysis to study asymmetric market behaviour. This model specifically zooms in on the leverage effect, a phenomenon in which negative returns exert a more pronounced influence than positive returns. By leveraging the GJR-GARCH (1, 1) model equation, which includes components for the conditional variance, a constant term, squared returns, and a dummy variable to differentiate between positive and negative shocks, analysts gain deeper insights into the dynamics of financial markets. This modelling approach proves instrumental in capturing the nuances of market volatility and risk, thus aiding in more informed decision-making processes within the realm of finance.

These mathematical expressions within the GARCH, EGARCH, and GJR-GARCH models provide a framework for understanding and modelling financial market volatility during the COVID-19 pandemic, capturing aspects of persistence, asymmetry, and leverage effects in market returns.

Augmented-Dickey Fuller unit root test

A series is said to be weakly or covariance stationary if its statistical properties such as
Mean, variance, autocovariance, etc., are all constant over time. In this study, we employ
Augmented Dickey Fuller (ADF) unit root test according to Dickey and Fuller (1979). The
The augmented Dickey-Fuller (ADF) unit root test constructs a parametric correction for
Higher-order correlation by assuming that the series follows an AR (p) process:

$rt = \theta 1rt{-}1 + \theta 2rt{-}2 + \cdots + \theta prt{-}p + \varepsilon t$ (3.9)

If $H0$: $\theta*$ = against the alternative $H1$: $\theta*$ <then rt contains a unit root. To test the null hypothesis, the ADF test is evaluated using the $t-$ statistics:

$$t_\theta = \frac{\theta^*}{SE(\theta^*)}$$

where $\theta*$ is the estimate of θ, and SE ($\theta*$) is the coefficient standard error.

Heteroskedasticity test

To test for heteroskedasticity or the ARCH effect in the residuals of cryptocurrency returns,
We apply the Lagrange Multiplier (LM) test according to Engle (1982). The procedure of
performing the Engle's LM test is to first obtain the residuals et from an ordinarleasttm squares regression of the conditional mean equation, which could be an AR, MA or
ARMA model that best fits the data. For an ARMA (1,1) model, the conditional mean
Equation is specified as

$rt = \phi 1rt{-}1 + \varepsilon t + \theta 1\varepsilon t{-}1$ (3.11)

where rt is the return series, $\phi 1$ and $\theta 1$ are the coefficients of the AR and terms, respectively terms
While εt is the random error term. Having obtained the residuals et, we then regress the
Squared residuals on a constant and q lags such as in the following equation:

$$e_t^2 = \alpha_o + \alpha_1 e_{t-1}^2 + \alpha_2 e_{t-2}^2 + \alpha_3 e_{t-3}^2 + \ldots + \alpha_q e_{t-q}^2 + v_t \quad (3.12)$$

The null hypothesis of no ARCH effect up to lag q is then formulated as follows:
$H0$: $\alpha1 = \alpha2 = \alpha3 = \cdots = \alpha q$ versus the alternative $H1$: $\alpha i > 0$ for at least one $i =$ 1,2,3, …, q.
There are two test statistics for the joint significance of the q-lagged squared residuals.
The F-statistic and the number of observations times R-squared ($nR2$) from the regression. The F-statistic is estimated as

$$F = \frac{SSR_o - SSR_1 / q}{SSR_1(n-2q-1)}$$

$$where\, SSR_1 = \sum_{t=q+1}^{T} e^2, SSR_0 = \sum_{t=q+1}^{T} (r_t^2 - r)^2 and\; r = \frac{1}{n}\sum_{t-1}^{T} r_t^2 \qquad (3.13)$$

$\hat{e}t$ is the residual obtained from the least squares linear regression, $\bar{r}$ is the sample mean of rt 2. The $nR2$ is evaluated against $\chi2(q)$ distribution with q degrees of freedom under $H0$. The decision is to reject the null hypothesis of no ARCH effect in the residuals of returns if the p-values of the F-statistic and $nR2$ statistic are less than $\alpha = 0.05$

Ljung-Box Q-statistics test for serial correlation

The Ljung-Box Q-statistic test is used for investigating the presence of serial correlation or autocorrelation in a time series. The test checks the following pair of hypotheses:
$H0$: $\rho k,1 = \rho k,2 = \cdots \rho k, T = 0$ (all lags' correlations are zero)
$H1$: $\rho k,1 \neq \rho k,2 \neq \cdots \rho k, T \neq 0$ (there is at least one lag with non-zero correlation).
The test statistics is given by

$$Q^{(LB)} = T(T+2)\sum_{k=1}^{h} \frac{pk}{T-k} \qquad (3.14)$$

$$where\; p_k^2 = (T\sum_{t=k+1}^{T} (\varepsilon_t^2 - \varepsilon^2)(\varepsilon_t^2 - \varepsilon^2),\; for\; \varepsilon^2 = T^{-1}\sum_{t=1}^{T} \varepsilon^2$$

Denotes the autocorrelation estimate of squared standardized residuals at k lags. where? is the sample size, Q is the sample autocorrelation at lag k. theoretically, the Q-statistic is asymptotically Chsquaredre distributed with degrees of freedom equal to the number of autocorrelations. We reject $H0$ if p-value is less than $\alpha = 0.05$ level of significance (Ljung and Box, 1978).

5. Model Specification

The following conditional heteroskedastic time series models are specified for this study.

6. The autoregressive conditional heteroskedasticity (ARCH) model

The Autoregressive Conditional Heteroskedasticity model of order q, ARCH (q) proposed by Engle (1982) without dummy my variable is given by:

$$rt = \mu t + \varepsilon t \qquad (3.15)$$

$$\varepsilon t = \sigma tet;\; et \sim N\,(0,1) \qquad (3.16)$$

$$\sigma_t^2 = \omega + \alpha_1\varepsilon_{t-1}^2 + \alpha_2\varepsilon_{t-2}^2 + ... + \alpha q\varepsilon_{t-q}^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \qquad (3.17)$$

where ε_t is the innovation/shock at day t and it follows the heteroskedastic error process, $\sigma^2 t$ is the volatility at day t (conditional variance), ε^2_{t-1} is the squared innovation at day t – I, ω is a constant term. A sufficient condition for the conditional variance to be positive is that the parameters of the model should satisfy the following constraints: $\omega > 0$, $\alpha i \geq 0$ for $i > 0$. The ARCH (1) process is defined by the following equations:

$$\sigma^2 t = \omega + \omega + \alpha_1 \varepsilon_{t-1}^2 \quad (3.18)$$

where $\omega > 0$ and $\alpha_1 \geq 0$. As the persistence (as measured by $\alpha 1$) increases towards unity, the process explodes.

7. The generalized autoregressive conditional heteroskedasticity (GARCH) model

Bollerslev (1986) extended the ARCH model of Engle (1982) to Generalised Autoregressive Conditional Heteroskedasticity (GARCH) model. A GARCH (p, q) process is specified as

$$rt = \mu_t + \varepsilon_t \quad (3.19)$$

$$\varepsilon t = \sigma_t e_t; \; et \sim N(0, 1) \quad (3.20)$$

$$\sigma t\ 2 = \omega \sum_{i=1}^{q} \alpha_i \varepsilon_{t-1}{}^2 + \sum_{j=1}^{p} \beta_i \sigma j \quad (3.21)$$

where ε_t is the innovation/shock at day t and it follow the heteroskedastic error process, σ_t^2 is the volatility at day t (conditional variance), ε_{t-i}^2 is squared innovation at day $t - i$, ω is a constant term, μ_t can be any adapted model for the conditional mean; p is the order of the autoregressive GARCH term; q is the order of the moving average ARCH term .

The GARCH (1,1) model is capable of capturing all the volatilities in any return series and is Defined as

$$\sigma t^2 = \omega + \omega + \alpha_1 \varepsilon^2{}_{t-1} + \beta_1 \sigma_{t-1}{}^2 \quad (3.22)$$

The requirements for stationarity in the GARCH (1, 1) model are that $\alpha 1 + \beta 1 < 1$, $\alpha 1 \geq 0$, $\beta 1 \geq 0$ and $\omega > 0$.

The mean or expected value of the GARCH (1,1) model is given as

$$E(\varepsilon_t^2) = \frac{\omega}{(1 - \alpha_1 - \beta_1)} \quad (3.23)$$

Under the stationarity assumptions and finite-fourth moments, the kurtosis ($g2$) of The GARCH (1,1) process is given by

$$g_2 = \frac{E(\varepsilon_t^4)}{E(\varepsilon_t^2)^2} = 3(\frac{1 + \alpha_1 + \beta_1}{1 - 2\alpha_1 \beta_1}) \quad (3.24)$$

The first-order autocorrelation function of the GARCH (1,1) process is approximately

$\rho 1 \approx \alpha 1 + 1\ 3\!\!/\ \beta 1$ (3.25)

and the autocorrelation function at lag k is approximately

$$\rho k \approx [\alpha 1 + 1/3\ \beta 1]\ [\alpha 1 + \beta 1]\ k{-}1. \quad (3.24)$$

From this, it is clear that the autocorrelation function still decreases exponentially (Bollerslev, 1988)

Modelling mean reversion using the GARCH (1,1) model

Although excessive volatility may be experienced in the financial markets from time to Time, it will eventually settle down to a long-run level. Given that the long level of variance εt for stationary GARCH (1,1) model is

$$\bar{\sigma}^2 = \frac{\omega}{(1-\sigma_1-\beta_1)}$$

In this case, volatility is always pulled towards this long-run level by rewriting the ARMA representation

$$\varepsilon_t^2 = \omega + (\alpha_1 + \beta_1)\varepsilon_{t-1}^2 + \mu_t - \beta_1\mu_{t-1} \quad (3.28)$$

as follows

$$(\varepsilon_t^2 - \frac{\omega}{(1-\sigma_1-\beta_1)}) = (\sigma_1+\beta_1)(\varepsilon_t^2 - \frac{\omega}{(1-\sigma_1-\beta_1)}) + \mu_t - \beta_1\mu_{t-1} \quad (3.25)$$

If the above equation is iterated k times, it can be shown that

$$(\varepsilon_{t+K}^2 - \frac{\omega}{(1-\sigma_1-\beta_1)}) = (\sigma_1+\beta_1)^k(\varepsilon_t^2 - \frac{\omega}{(1-\sigma_1-\beta_1)}) + \eta_{t-k}$$

where η_t is the moving average process since $(\alpha 1 + \beta 1) < 1$ the stationary GARCH (1,1) model, $(\alpha_1 + \beta_1)^k \rightarrow 0$ as $k \rightarrow \infty$. Although at time t there may be a large deviation between ε_t^2 and the long-run variance $\varepsilon_t^2 = \omega/(1 - \sigma 1 - \beta 1)$ will approach zero on average as k gets large. That is, the volatility mean reverts to its long-run level $\omega/(1 - \sigma 1 - \beta 1)$. In contrast, if $\omega/ (1 - \sigma 1 - \beta 1) > 1$ and the GARCH model is non-stationary, the volatility will eventually explode to infinity as $k \rightarrow \infty$. Similar arguments can be easily constructed for the GARCH (p, q) model (Kuhe & Audu, 2016).

Model order selection using information criteria

GARCH model order and error distribution selection involves selecting a model order that minimizes one or more information criteria evaluated over a range of model orders. In this work, we employed the Schwarz information criterion (SIC) due to (Schwarz, 1978).

The criterion is given as

$$SIC(P) = -2\ln(L) + P\ln(T) \quad (3.26)$$

where P is the number of free parameters to be estimated in the mode and, T is the number of observations and L is the maximum likelihood function for the estimated model defined by:

$$L = \prod_{i=1}^{n}(\frac{1}{2\pi\sigma_t^2})^{\frac{1}{2}} \exp\left[-\sum_{i=1}^{n}\frac{(yi-f(x)^2}{2\sigma_t^2}\right] \quad (3.27)$$

in $$L = in\prod_{i=1}^{n}(\frac{1}{2\pi\sigma_t^2})^{\frac{1}{2}} \exp\left[-\frac{1}{2}\sum_{i=1}^{n}\frac{(yi-f(x)^2}{2\sigma_t^2}\right] \quad (3.28)$$

Thus, given a set of estimated GARCH models for a given set of data, the preferred model is the one with the minimum information criterion and the highest log likelihood value.

8. Error distribution for modelling volatility

To estimate the time-varying volatility in the cryptocurrency returns and account for the excess kurtosis and fat tails that are present in the residuals of the return series, we model the error term in the GARCH models with normal (Gaussian) distribution, Student's t-Distribution, and Generalised Error Distribution (GED). These distributions are appropriate to capture the excess kurtosis and the skewness in the residuals return series (Greene, 2010).

1. *Normal (Gaussian) Distribution* (ND): The normal distribution is given by

$$f(z) = \frac{1}{\sqrt{2\pi}} e^{\frac{-z^2}{2}}, -\infty < z < \infty$$

The normal distribution to the log likelihood for observation t is given as:

$$Lt= \frac{-1}{2}\log(2\pi) - \frac{1}{2}\log\sigma_t^2 - \frac{1}{2}(y_t - X_t\theta)^2$$

(ii) Student's t-Distribution (STD): The student's t-distribution is given as:

$$F(z)= \frac{\Gamma(\frac{v+1}{2})}{\sqrt{v\pi\Gamma(\frac{v}{2})}}(1+\frac{z^2}{v})^{-(\frac{v+1}{2})}, -\infty < z < \infty$$

For student's t −distribution, the log-likelihood contributions are of the form:

$$L_t = \frac{1}{2}\log[\frac{\pi(v-2)\Gamma(\frac{v}{2})^2}{\Gamma(\frac{(v+1)}{2}}] - \frac{1}{2}\log\sigma_t^2 - \frac{(v+1)}{2}\log[1+\frac{(y_{t-Xt\theta})^2}{\sigma_t^2(v-2)}$$

where $\Gamma(.)$ is the gamma function. This distribution is always fat-tailed and produces Better fit than the normal distribution for most asset return series. The degree of freedom $v > 2$ controls the tail behaviour. The distribution is only well defined if $v > 2$becausee the variance of a student's-t with $v \leq 2$ is infinite, that is, the t −distribution approaches the normal distribution as $v \to \infty$.

9. Estimation of the GARCH models

There are many methods used in estimating the parameters of volatility models, but in this work, we shall restrict ourselves to the maximum likelihood estimation and quasi-maximum likelihood estimation.

We implemented the maximum likelihood method with Gaussian errors and quasi-maximum likelihood estimation with non-Gaussian errors (Student-t distribution and Generalised Error Distribution (GED)) in this research work. This helps us to provide a general framework for the issue of estimating (GARCH-type models and requires the need for the regression model with conditionally heteroskedastic error terms to be investigated.

10. Maximum likelihood estimation of the symmetric GARCH models

Estimating the ARCH and GARCH models using Maximum likelihood estimation is more efficient in the sense that the estimated parameters converge to their population counterparts at a faster rate (Greene, 2010).

Consider a simple GARCH (1,1) specification:

$rt = \mu t + \varepsilon t; \varepsilon t = \sigma t e t, et{\sim}N$ (0, 1)

$\sigma t2 = \omega + \alpha 1\varepsilon t{-}1\ 2 + \beta 1\sigma t{-}1$

Since the errors are assumed to be conditionally i.i.d. normal, maximum likelihood is a natural choice to estimate the unknown parameters, $\boldsymbol{\theta}$ which contain both the mean and variance parameters. The normal likelihood for the T independent variables is:

$$f(r;\theta) = \prod_{t=1}^{T}(2\pi\sigma_t^2)^{\frac{1}{2}}\exp(\frac{(r_t-\mu_t)^2}{2\sigma_t^2}$$

and the normal log-likelihood function is:

$$l(\boldsymbol{r};\boldsymbol{\theta}) = \sum_{t-1}^{T} -\frac{1}{2}\log(2\pi) - \frac{1}{2}\log(\sigma_t^2) - \frac{(r_t-\mu_t)^2}{2\sigma_t^2}$$

If the mean is set to zero, the log-likelihood simplifies to

$$l(\boldsymbol{r};\boldsymbol{\theta}) \; (\sum_{t-1}^{T} -\frac{1}{2}\log(2\pi) - \frac{1}{2}\log(\sigma_t^2) - \frac{(r_t^2}{2\sigma_t^2} \qquad (3.44)$$

and is maximized by solving the first-order conditions.

$$\frac{\partial l(r;\theta)}{\partial \sigma_t^2} = \sum_{t-1}^{T} \frac{1}{2\sigma_t^2} + \frac{r_t^2}{2\sigma_t^4} = 0 \qquad (3.45)$$

which can be rewritten to provide some insight into the estimation of ARCH models,

$$\frac{\partial l(r;\theta)}{\partial \sigma_t^2} = \sum_{t-1}^{T} \frac{1}{2\sigma_t^2} + \frac{r_t^2}{2\sigma_t^4} = 0 \qquad (3.46)$$

This expression clarifies that the parameters of the volatility are chosen to make $(\frac{r_t^2}{\sigma_t^2} - 1)$ as close to zero as possible. If $Et-1$ $\frac{r_t^2}{\sigma_t^2} - 1)$ = 0, and so the volatility is correctly specified the scores of the log-likelihood have expectation zero since

$$[\; [E_{t-1}(\frac{r_t^2}{\sigma_t^2} - 1)] = E[E_{t-1}[\frac{1}{\sigma_t^2}(\frac{r_t^2}{\sigma_t^2} - 1)]] = E_{t-1}[\frac{1}{\sigma_t^2}(\frac{r_t^2}{\sigma_t^2} - 1)]]$$

$$= E\;[\frac{1}{\sigma_t^2}(0)] = 0$$

These first-order conditions are not complete since ω, $\alpha 1$, and $\beta 1$, not $\sigma t2$ are the parameters of a GARCH (1,1) model and

11. Justification of the Method

To justify the chosen method, the study will discuss the use of three measures of volatility: standard deviation, skewness, and kurtosis, with the standard deviation being the most commonly used measure. The study will also use the Jarque-Bera test to examine the goodness of fit for the distribution of returns, indicating the presence of fat-tail phenomena in the financial markets.

The GARCH family of models is employed to account for dynamic volatility phenomena and volatility clustering in modelling financial returns volatility. The GARCH (1, 1) model is recommended for modelling the conditional volatility of market returns, as it is capable of capturing the volatile behaviour of financial assets during the pandemic. Additionally, the GJR-GARCH model is used to examine the asymmetric behaviour of financial market returns, specifically focusing on the leverage effect where investor reaction towards negative returns is more pronounced.

In conclusion, the method chosen in the Study is justified based on the need to understand the dynamics of financial market volatility during the COVID-19 pandemic. By utilising GARCH models and analysing various measures of volatility, the study provides valuable insights into the behaviour of financial assets during crises, which can be beneficial for investors and policymakers in constructing portfolios and strategizing for future economic scenarios.

12. Data Presentation

This Section presents the results of the data analysis of this study. The section particularly hinges on the presentation of the results of the Summary Statistics for the selected financial assets, graphical examination of the series, unit root test and heteroskedasticity test results.

13. Descriptive Statistics and Normality Measures of the Selected Financial Assets

To understand the descriptive and distributional characteristics of the selected financial assets, summary statistics such as the daily mean and standard deviation as well as normality measures such as skewness, kurtosis, Minimum, maximum and Jarque-Bera statistics have been computed and presented in Table .1

Table 1. *Summary Statistics for the selected financial assets*

Particulars	Bitcoin	EUR	S&P 500	Gold	Crude Oil	Sugar
Whole period						
Mean	0.003875	0.000103	0.000712	0.000561	0.000503	0.000512181
Standard Deviation	0.046004	0.003986	0.015302	0.01076	0.046245	0.017879922
Kurtosis	5.782102	4.008026	16.1689	5.736385	47.81848	1.605894798
Skewness	−0.379280	−0.385170	−1.03143	−0.15575	−2.74082	0.10688875
Range	0.518336	0.042611	0.217335	0.10748	0.891307	0.155743422
Minimum	−0.315290	−0.028140	−0.12765	−0.05121	−0.57167	−0.078285363
Maximum	0.203046	0.014467	0.089683	0.056266	0.319634	0.077458059
Jarque-Bera Test	904.27	442.44	7078.9	877.35	61768	69.216
Count	650	650	650	650	650	650
Before COVID-19						
Mean	0.002273	0.000016	0.000231	0.000793	−0.00125	0.00002700
Standard Deviation	0.042580	0.003403	0.011625	0.008599	0.028384	0.01546058
Kurtosis	3.685524	1.655074	9.873348	9.734605	31.4296	2.55831721
Skewness	0.297774	0.294543	−0.966510	0.145929	−2.80747	0.48522149
Range	0.362072	0.026953	0.127414	0.103186	0.41915	0.13021202
Minimum	−0.159030	−0.01261	−0.079010	−0.04877	−0.28221	−0.05275396
Maximum	0.203046	0.014345	0.048403	0.054414	0.136944	0.07745805
Jarque-Bera Test	181.3	39.815	1325.2	1240.6	13378	97.32
Count	325	325	325	325	325	325
During Covid 19						
Mean	0.005478	0.00019	0.001192	0.00033	0.002259	0.00099736
Standard Deviation	0.049205	0.004498	0.01826	0.012564	0.058924	0.02002169
Kurtosis	6.920719	4.253854	14.05538	3.665246	34.35576	0.95215866
Skewness	−0.84048	−0.69099	−1.01749	−0.21382	−2.41754	−0.09999114
Range	0.506817	0.042611	0.217335	0.10748	0.891307	0.14083676
Minimum	−0.31529	−0.02814	−0.12765	−0.05121	−0.57167	−0.07828536
Maximum	0.191527	0.014467	0.089683	0.056266	0.319634	0.06255140
Jarque-Bera Test	663.4	261.13	2642.5	177.05	15794	11.978
Count	325	325	325	325	325	325

Table 1 shows the price trends and return fluctuations of the financial markets. From the analysis of the data, an extensive decline has been observed in the price of the S&P 500 index, Crude Oil, and Sugar in March 2020. Additionally, the price of Bitcoin experienced a massive shock in May 2021. The returns graphs also show a high level of fluctuations at the beginning of the COVID-19 pandemic. Bitcoin and crude oil showed a high level of volatility during COVID-19, ranging from −0.31 to 0.19 and −0.57 to 0.31, respectively. Moreover, the volatility clustering can be seen in the return's graphs of the financial markets.

14. Time Plots of daily Selected Financial Markets

The time plots of daily cryptocurrency prices presented in Figures 1 suggests that the series have means and variances that change with time and the presence of a trend indicating that the series are not covariance stationary. The time plots of the daily cryptocurrency log return series presented in Figures 2 suggests that the series have constant means and variances with the absence of a trend, indicating that they are covariance stationary. The time plots of the cryptocurrency log returns also indicate that some periods in the plots are more clustered than others as large changes in the digital returns tend to be followed by large changes and small changes are followed by small changes. This phenomenon is described as volatility clustering. Volatility clustering is more noticeable in Cardano (ADA), Binance (BNB), Ethereum (ETH), Ripple (XRP), Stellar (XLM), Polygon (MATIC), and Chainlink (LINK) cryptocurrency returns.

Volatility clustering as one of the characteristic features of financial time series was first noticed in studies conducted independently by Mandelbrot (1963), Fama (1965) and Black (1976), when they observed the occurrence of large changes in stock prices being followed by large changes in stock prices of both positive and negative signs and the occurrence of small stock price changes being followed by periods of small changes in prices. Sequel to this result, numerous researchers, including Poterba and Summer (1986), Tse (1991), Najand (2002), Emenike and Aleke (2012) and Ezzat (2012), among others, have documented evidence in the literature proving that financial time series normally exhibit volatility clustering and leptokurtosis

Figure 1. Price trends in the financial markets over the period of November 27, 2018 to May 21, 2023.

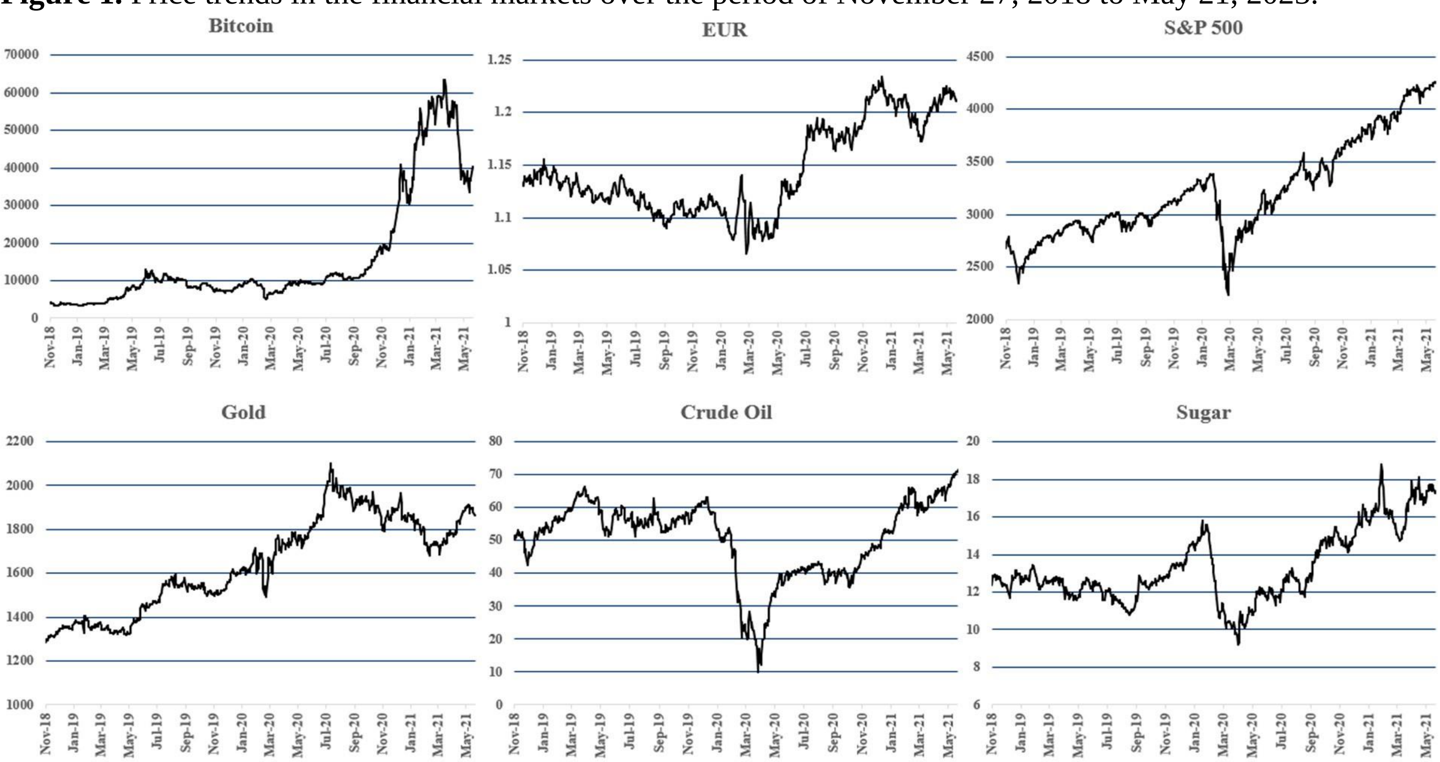
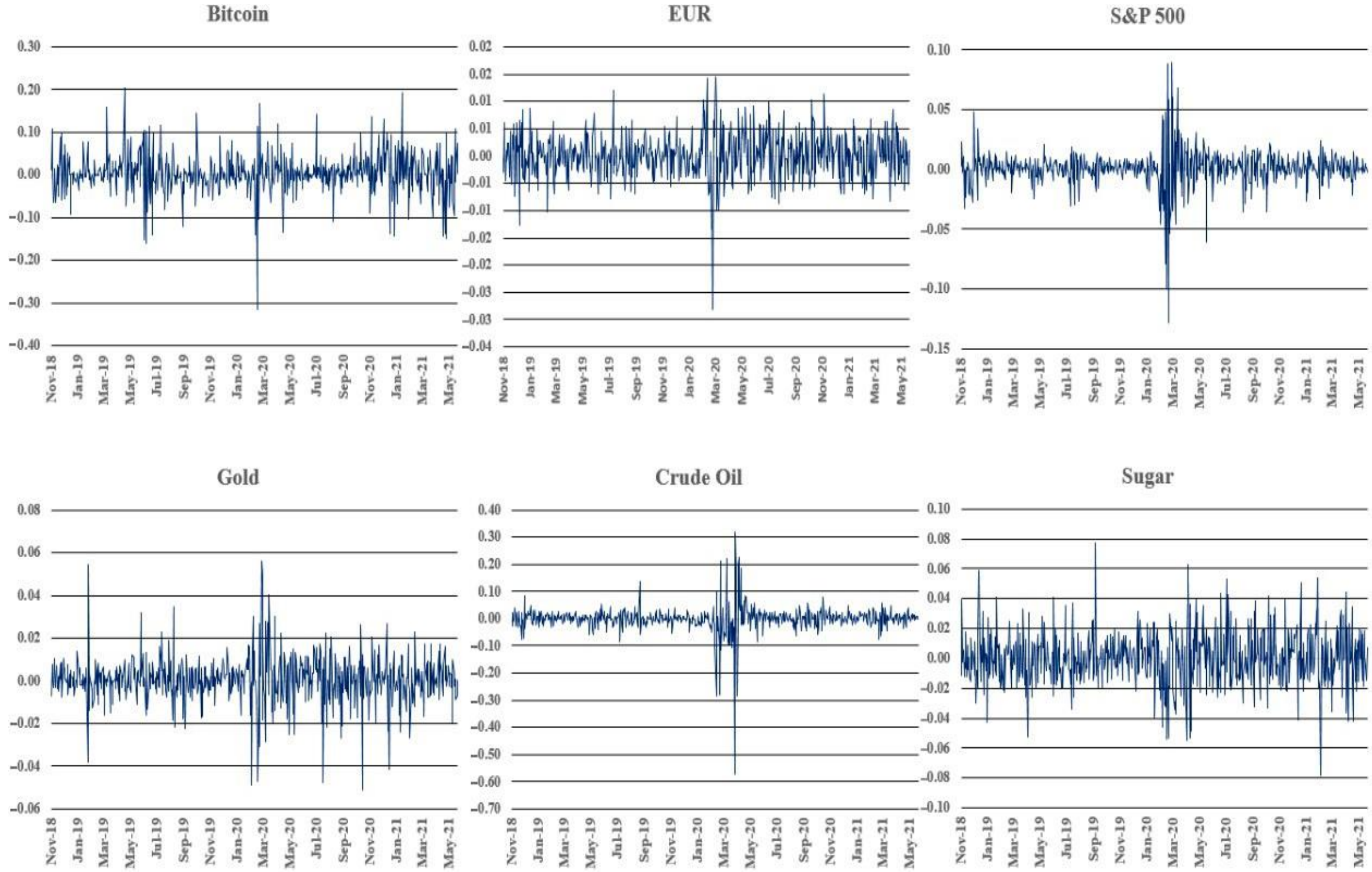


Figure 2. Returns fluctuations in the financial markets over the period of November 27, 2018 to May 21, 2023



15. Data Analysis and Results

This section looks at the data analysis and the results of the data analysis.

16. Augmented Dickey–Fuller test results for the selected financial assets

The Augmented Dickey–Fuller test results for the selected financial assets are computed and presented in table 2

Particulars	BTC	EUR	S&P 500	Gold	Crude Oil	Sugar
ADF Value	−17.8 ***	−16.68 ***	−17.765 ***	−18.078 ***	−19.99 ***	−17.373 ***
Probability Value	0.01	0.01	0.01	0.01	0.01	0.01

Note: *** shows the 1% significance level

Table 2 provides a comprehensive depiction of the outcomes derived from the Augmented Dickey–Fuller (ADF) test, a widely used method for assessing the stationarity of time series data. Notably, the ADF values presented therein indicate a profound significance at the 1% critical level across all assets scrutinised in the study. This statistical significance underscores a crucial finding: the returns series of the selected assets exhibit stationary characteristics, thereby yielding crucial insights into their underlying dynamics. Consequently, this empirical evidence both confirms and refutes the null hypothesis positing the existence of a unit root within the returns series, thus advancing our understanding of the fundamental properties governing asset price movements.

Furthermore, the robustness of these results underscores the reliability and validity of the ADF test in discerning the stationarity properties of financial time series data. By demonstrating significant ADF values at a stringent critical level, Table 2 not only substantiates the stationary nature of the returns series but also underscores the efficacy of the chosen analytical framework. This validation carries profound implications for financial modelling and decision-making processes, as it provides stakeholders with actionable insights into the long-term behaviour of the selected assets. Consequently, these findings serve as a vital foundation for informed investment strategies and risk management practices, empowering market participants to navigate the complexities of financial markets with heightened precision and confidence.

17. Estimation of the GARCH Models

Table 3: Show the results based on the GARCH models before the COVID-19 Pandemic March (2020).

Asset Class	Model	μ	ω	α(ARCH)	β (GARCH)	α+β	γ (Gamma),	Log Likelihood	AIC
BTC	GARCH (1, 1) GJR- GARCH(1 ,1) EGARCH (1, 1)	0.001575 0.001534 0.001244	0.000062 0.000054 - 0.174239 *	0.124018* 0.143439* 0.036888	0.8749 82*** 0.8876 96*** 0.9721 07***	0.999 1.031 135 1.008 995	- - 0.0614 79 0.2584 52***	619.88 94 620.10 43 624.16 17	−3.7778 -3.7729 -3.7979
EUR/USD	GARCH (1, 1) GJR- GARCH(1 ,1) EGARCH (1, 1)	-0.000093 0.00003 0.000001	0.000001 0.000001 - 1.058863 **	0.076241 0.118079** 0.098288**	0.8455 16*** 0.8949 21*** 0.9069 61***	0.921 757 1.013 1.005 249	- - 0.1148 15 0.1165 47***	1398.0 76 139897 1399.5 02	-8.5666 -8.566 -85692
S&P 500	GARCH (1, 1) GJR- GARCH(1 ,1) EGARCH (1, 1)	0.001054 0.000627 0.000445	0.000004 0.000004 *** - 0.575678 **	0.247109*** 0 -0.310019**	0.7298 3*** 0.7663 9*** 0.9407 52***	0.976 939 0.766 39 0.630 733	- 0.3772 6*** 0.0953 04***	1104.3 23 1115.6 77 1120.2 24	-6.7589 -6.8226 -6.8506
Gold	GARCH (1, 1) GJR- GARCH(1 ,1) EGARCH (1, 1)	0.000738 0.000776 0.000563	0 0 - 3.918943 **	0.002481 0.009621 -0.057158	0.9964 7*** 0.9998 03*** 0.5920 84***	0.998 951 1.009 424 0.534 926	- - 002108 2** 0.4127 96***	1143.2 98 1143.4 38 1146.2 5	-6.9988 -6.9935 -7.0108
Crude Oil	GARCH (1, 1) GJR- GARCH(1 ,1) EGARCH (1, 1)	-0.000072 -0- 000989 -0.001059	0.000043 0.000015 *** - 0.178794 **	0.1222254* 0 -0.14327***	0.8273 23*** 0.9194 19*** 0.9758 97***	0.949 577 0.919 419 0.832 627	- 0.1303 78*** 0.0301 63**	709.14 03 795.79 55 797.57 16	-4.8255 -4.8541 -4.8651
Sugar	GARCH (1, 1) GJR- GARCH(1 ,1) EGARCH (1, 1)	-0.00005 -0.000144 -0.00019	0 0.000052 -1.69632*	0 0 -0.12458*	0.999* ** 0.6781 75*** 0.7980 2 ***	0.999 0.678 175 0.673 44	- 0.2340 51* 0.2266 7*	906.48 32 911.28 45 911.06 19	-5.5414 -5.5648 -5.5653

Note: *** refers to the 1% Significance level, **refers to the 5% Significance level, and *refers to the 10% Significance level.

Table 4: Show the results based on the GARCH models during the COVID-19 Pandemic March to June (2021).

Asset Class	**Model**	**μ**	**ω**	**α(ARCH)**	**β (GARCH)**	**α+β**	**γ (Gamma),**	**Log Likelihood**	**AIC**
BTC	GARCH (1, 1) GJR- GARCH(1,1) EGARCH (1, 1)	0.0051 33 0.0051 36 0.0052 3	0.00004 6 0.00003 6 - 0.067	0.086228* ** 0.096668* ** 0.035923	0.912772* ** 0.919377* ** 0.98845	0.999 1.0160 45 1.0160 45	- -0.033637 0.191335* **	575.45 89 575.67 74 577.34 27	- 3.5044 - 3.4996 - 3.5098
EUR/U SD	GARCH (1, 1) GJR- GARCH(1,1) EGARCH (1, 1)	0.0002 15 0.0001 78 0.0002 48	0 0 - 0.7275* *	0.009999 0.002145 -0.023663	0.986357* ** 0.987274* ** 0.933762* **	0.9963 56 0.9894 19 0.9100 99	- 0.012225 0.136151* **	1309.7 44 1310.4 2 1311.0 29	-8.023 -8.021 - 8.0248
S&P 500	GARCH (1, 1) GJR- GARCH(1,1) EGARCH (1, 1)	0.0013 18 0.0010 23 0.0008 02	0.00000 7 0.00000 8 - 0.42321 2*	0.21278** * 0.102173* -0.104427	0.754481* ** 0.765049* ** 0.952725* **	0.9672 61 0.8672 22 0.8482 98	- 0.011201 0.138397	993.60 05 995.30 24 993.26 19	- 6.0775 - 6.0819 - 6.0693
Gold	GARCH (1, 1) GJR- GARCH (1,1) EGARCH (1, 1)	0.0004 68 0.0004 59 0.0003 95	0 0 - 0.3008* *	0.021306 0.012131 -0.017036	0.973694* ** 0.977937* ** 0.966609* **	0.995 0.9900 68 0.9495 73	- 0.296711* ** 0.250228* **	998.68 12 998.87 52 998.99 16	- 6.1088 - 6.1038 - 6.1046
Crude Oil	GARCH (1, 1) GJR- GARCH (1,1) EGARCH (1, 1)	0.0025 34 0.0016 41 0.0016 99	0.00003 7 0.00003 3 - 0.2203* *	0.21892** * 0.000142 - 0.177449* *	0.762427* ** 0.815486* ** 0.970494* **	0.9813 47 0.8156 28 0.7930 45	- 0.296711* ** 0.250228* **	705.12 72 711.42 22 710.15 45	- 4.3023 - 4.3349 - 4.3271
Sugar	GARCH (1, 1) GJR- GARCH (1,1) EGARCH (1, 1)	0.0011 86 0.0010 87 0.0012 29	0.00010 8 0.00000 8** - 1.74525 4	0.117035 0.000002 0.040641	0.603234* 0.969072* ** 0.778879*	0.7202 69 0.9690 74 0.8195 2	- 0.018919 0.207247	818.78 32 815.98 88 818.27 76	- 5.0017 - 4.9784 - 4.9925

Note: *** refers to the 1% Significance level, **refers to the 5% Significance level, and *refers to the 10% Significance level.

The objective of the study is to investigate the impact of the COVID-19 pandemic on financial market volatility and analyse volatility dynamics using appropriate econometric models. The results obtained from Tables 1 and 2 offer valuable insights into the behaviour of various financial assets during and before the pandemic period.

EGARCH (1, 1) model parameters, it is evident that each financial market representative exhibits a long-term memory effect and an asymmetric effect at different significance levels. This finding suggests that the volatility of financial markets tends to persist over time, indicating a degree of predictability in market movements. Additionally, the observed asymmetric behaviour, particularly during the COVID-19 pandemic, highlights the sensitivity of financial markets to adverse shocks and the presence of heightened volatility during times of crisis. Statistical significance plays a crucial role in interpreting the coefficients estimated in the econometric models. In both Table 1 and Table 2, significance levels (***, **, *) are provided to indicate the statistical significance of the coefficients at different thresholds. For instance, a coefficient marked with *** indicates significance at the 1% level, implying a high degree of confidence in the estimated relationship. Conversely, a coefficient marked with * suggests significance at the 10% level, indicating a lower degree of confidence. Analysing the significance levels of each coefficient allows researchers to discern the robustness of the estimated relationships and make informed interpretations about the underlying dynamics of the financial markets. In the context of the study's objectives, significant coefficients provide evidence of the impact of the COVID-19 pandemic on financial market volatility and offer insights into the mechanisms driving market dynamics during times of crisis. Now, let us delve into the specific findings highlighted in the interpretation provided. The mention of BTC exhibiting the highest volatility persistence ($\beta = 0.98$) during the pandemic period underscores the heightened uncertainty and turbulence experienced in the cryptocurrency market during the COVID-19 crisis. This finding suggests that BTC prices were particularly sensitive to market shocks and exhibited a strong tendency to persist in their movements during this period.

Similarly, the observation of crude oil demonstrating significant volatility persistence ($\beta = 0.97$) during the pandemic highlights the impact of external factors such as geopolitical tensions and changes in global demand on oil prices. The persistence of volatility in the crude oil market underscores the challenges faced by oil producers and consumers alike in navigating uncertain market conditions during the pandemic. Furthermore, the identification of a leverage effect in the gold commodity market before the COVID-19 pandemic, with a leverage coefficient of 0.41, suggests that gold prices were sensitive to changes in market sentiment and exhibited asymmetric behaviour in response to positive and negative shocks. This asymmetry in gold prices underscores the role of gold as a safe-haven asset during times of economic uncertainty, with investors flocking to gold as a store of value in turbulent times. Moreover, the comparison of volatility persistence in the gold commodity market before and during the COVID-19 pandemic reveals a notable increase in volatility persistence ($\beta = 0.96$) during the pandemic period compared with that before the pandemic ($\beta = 0.59$). This finding suggests that the COVID-19 pandemic had a significant impact on the gold market, with increased volatility reflecting heightened uncertainty and risk aversion among investors.

Table 5: Show the results based on the GARCH models for the whole period (November 2018 to June 2023)

Asset Class	Model	μ	ω	α(ARCH)	β (GARCH)	α+β	γ (Gamma)	Log Likelihood	AIC
BTC	GARCH (1, 1)	0.0033	0.000046	0.098295***	0.900705***	0.999	-	1193.305	-3.6532
	GJR-GARCH (1,1)	0.003312	0.00004	0.108002***	0.907544***	1.015546	-0.031982	1193.576	-3.651
	EGARCH (1, 1)	0.002644	-0.107781*	0.029598***	0.98199***	1.011588	0.237742***	1198.772	-3.667
EUR/USD	GARCH (1, 1)	0.000057	0.000001	0.070414	0.886033***	0.956447	-	2706.761	-8.31
	GJR-GARCH (1,1)	0.000099	0	0.082489	0.919543***	1.002032	-0.056764	2707.987	-8.3107
	EGARCH (1, 1)	0.000101	0.430652**	0.043688	0.961453***	1.005141	0.134607***	2708.079	-8.311
S&P 500	GARCH (1, 1)	0.001122	0.000004	0.224243**	0.755825***	0.980068	-	2100.47	-6.4445
	GJR-GARCH(1,1)	0.000776	0.000005	0.056481	0.774716***	0.831197	0.284695***	2109.279	-6.4685
	EGARCH (1, 1)	0.000617	0.365606***	-0.168038**	0.960603***	0.792565	0.266212***	2108.935	-6.4675
Gold	GARCH (1, 1)	0.000799	0.000003	0.076819	0.92117***	0.997989	-	2139.454	-6.5645
	GJR-GARCH (1,1)	0.000793	0.000003	0.071891	0.921787***	0.993678	0.00818	2139.469	-6.5614
	EGARCH (1, 1)	0.000705	0.16336**	0.009072	0.98167***	0.990742	0.172849	2139.152	-6.5605
Crude Oil	GARCH (1, 1)	0.001229	0.000041**	0.163904	0.796179***	0.960083	-	1492.581	-4.5741
	GJR-GARCH(1,1)	0.000472	0.000034**	0.002758	0.839875***	0.842633	0.220441***	1502.661	-4.602
	EGARCH (1, 1)	0.000539	0.234677*	-0.145662**	0.968419***	0.822757	0.200642***	1500.59	-4.5957
Sugar	GARCH (1, 1)	0.00072	0.000043*	0.121029**	0.745903***	0.866932	-	1721.499	-5.2785
	GJR-GARCH (1,1)	0.00059	0.000007**	0	0.955467***	0.955467	0.050876***	1720.485	-5.2723
	EGARCH (1, 1)	0.000592	-0.772434	-0.0231	0.904781***	0.881681	0.224624***	1722.728	-5.2792

Note: *** refers to the 1% Significance level, **refers to the 5% Significance level, and *refers to the 10% Significance level.

Moreover, Table 4 refers to the empirical results of the different GARCH family models during the COVID-19 pandemic. Our basic emphasis is on the selection of the best-fit GARCH model that determines the volatilities of the representatives of the six financial markets under observation. Based on the numerical results provided by the AIC, GARCH (1, 1) is regarded as the best model for describing the volatilities of Gold and Sugar; meanwhile, GJR-GARCH (1, 1) is the most suitable model in terms of modelling the volatilities of crude oil and S&P 500; the volatilities of BTC and EUR are best modelled by E-GARCH (1, 1). Concerning the E-GARCH (1, 1) results, both the BTC and EUR returns series show high persistence behaviour due to the fact that the sum of the ARCH and GARCH parameters are either greater than 1 or close to it (1.024373, 0.910099). This high persistence is probably the result of the COVID-19 pandemic. In addition, both of them also show significant asymmetric effects (gamma) at the 1%, 5%, and 10% significance levels because of the drastic economic impacts. In contrast, the returns volatilities of S&P 500 and Crude Oil based on the GJR-GARCH (1, 1) model also show persistent behaviour but are lower than that of BTC and EUR; moreover, S&P 500 shows a significant asymmetric effect at the 5% and 10% significance levels and Crude Oil exhibits a significant asymmetric effect at the 1%, 5%, and 10% significance levels. In contrast, the Gold and Sugar returns series exhibit persistent behaviour along with the symmetric effect; however, gold shows more persistent behaviour ($\alpha + \beta = 0.955$) when compared to Sugar ($\alpha + \beta = 0.720269$); the reason might be that COVID-19 had a negligible effect on Gold and Sugar. On the other hand, Metal has been considered a safe haven financial instrument during various forms of financial crises (Bouri et al. 2020; Jareño et al. 2020; Selmi et al. 2018). Studies confirm that the price of gold increased during the global financial crisis, whereas the prices of other financial assets declined drastically (Beckmann et al. 2015). Furthermore, Conlon and McGee (2020) found that Bitcoin did not act as a safe-haven instrument during the COVID-19 outbreak. Klein et al. (2018) also reported that Bitcoin returns have an asymmetric response to market shocks.

Table 5 illustrates the application of GARCH (1, 1), GJR-GARCH (1, 1), and E-GARCH (1, 1) on the representatives of the six financial markets for the entire period. According to the AIC values, concerning the returns series of the Gold commodity, GARCH (1, 1) is the best-suited model for capturing the volatility. The results suggest that the Gold returns series possess symmetric phenomena and high persistent behaviour ($\alpha + \beta = 0.997989$).

However, for most of the asset returns, including BTC, EUR, and Sugar, the E-GARCH (1, 1) model is the most suitable model in terms of determining their volatilities. Moreover, among them, BTC and EUR exhibited the strongest persistence, whereas all three showed a significant asymmetric effect at the 1%, 5%, and 10% significance levels. In addition, GJR-GARCH (1, 1) was selected as the best model to capture the volatilities of the Crude Oil and S&P 500 index returns. Additionally, a significant asymmetric effect was present in the return's series of the Crude Oil and S&P 500 index returns at a significance level of 1%, 5%, and 10%. Meanwhile, high persistent behaviour was shown by the S&P 500 returns and the Crude Oil returns. Overall, after analysing the results for the three different periods, it can be concluded that a single model is not sufficient to model the volatilities of the selected financial assets. Each model provides different estimations for the different periods, i.e., E-GARCH (1, 1) provides a better fit for the assets under observation before the COVID-19 pandemic.

The model fitness changes during the COVID-19 pandemic, that is volatilities of Gold, and Sugar are modelled by GARCH (1, 1) showing persistent behaviour, S&P 500, and Crude Oil are modelled by GJR-GARCH (1, 1) exhibiting significant leverage effect and persistence phenomena. Moreover, E-GARCH (1, 1) captures the leverage effect and persistent behaviour of BTC and EUR. In contrast, different results are shown for the whole period, where only the returns series of the Gold commodity was modelled by GARCH (1, 1), showing high persistence with no leverage effects, whereas the BTC, EUR, and Sugar volatilities are described by E-GARCH (1, 1), exhibiting significant leverage effects and persistence effects; furthermore, the S&P 500 and Crude Oil returns volatilities are captured by GJR-GARCH (1, 1), addressing persistence behaviour and leverage phenomena.

18. Discussion of the Findings

The COVID-19 pandemic had a catastrophic influence on the financial markets (Ali et al. 2020; Aslam et al. 2020a; Haroon and Rizvi 2020; Sansa 2020), and the volatility behaviour of the financial returns was shaken by this crisis. In this study, we investigated the market volatility of six financial markets during the COVID-19 pandemic by adopting three GARCH family models [GARCH (1, 1), GJR-GARCH (1, 1), and EGARCH (1, 1)]. The findings of the study indicate that the exponential GARCH model is appropriate for BTC and EUR, while GJR-GARCH (1, 1) is appropriate for S&P 500 and Crude Oil. These findings are supported by Iqbal et al. (2021), who reported that, for modelling volatilities, the EGARCH model outperforms the traditional GARCH model. The volatility persistence of all financial markets was high during the COVID-19 pandemic. The findings of this study also confirm the insignificant asymmetric effect in the volatility of the Gold returns during the pandemic. However, Crude Oil had a significant positive asymmetric effect during this pandemic. Moreover, Shehzad et al. (2021) also reported that crises like COVID-19 have abruptly affected both the stock and oil markets. Furthermore, the increase in the volatility of the financial markets generated a fear of losing money among investors due to the COVID-19 pandemic (Chen et al. 2020).

This study makes a significant contribution to the existing literature; this is the first attempt to highlight the volatility behaviour of all the major financial assets from the six major financial markets during the COVID-19 pandemic. A very significant question arises: were all the financial markets affected by the tragic pandemic? Despite the new phase of COVID-19 cases and the extensive fluctuation in the financial markets across the world, the markets indicate a recovery pattern. Given the uncertainty, it is very challenging to predict the long-term financial impact of COVID-19. The cryptomarket experienced a massive crash during the COVID-19 pandemic. The findings also revealed potential evidence of a volatility trend over the period and a high level of volatility persistence for Bitcoin. During the COVID-19 pandemic, a significant increase was reported in the volatility of Bitcoin.

This can be explained by the irrational behaviour of investors, which leads to speculation in the financial market. In a speculative bubble situation, the news of prices can affect irrational investors' decisions, which leads to catastrophic results in the market like a virus.

19. Summary

The COVID-19 pandemic has left an indelible mark on the global financial landscape, its influence reverberating through markets worldwide. Studies such as those by Ali et al. (2020), Aslam et al. (2020a), Haroon and Rizvi (2020), and Sansa (2020) have underscored the profound impact of the crisis on financial markets, with volatility becoming a defining characteristic of financial returns during this period. In response, researchers have delved into understanding market volatility during the pandemic, employing sophisticated modelling techniques like the GARCH family models.

The investigation into market volatility during the COVID-19 pandemic revealed nuanced patterns across various financial markets. Notably, the exponential GARCH model emerged as fitting for assets like Bitcoin (BTC) and the Euro (EUR), while the GJR-GARCH (1, 1) model proved suitable for the S&P 500 and Crude Oil. These findings, consistent with the research by Iqbal et al. (2021), shed light on the efficacy of different models in capturing volatility dynamics during crises. Furthermore, the study highlighted the persistence of volatility across all markets, underscoring the pervasive uncertainty engendered by the pandemic.

Despite the severity of the pandemic's impact, not all markets responded uniformly. While insignificant asymmetric effects were observed in Gold returns, Crude Oil exhibited a significant positive asymmetric effect during the crisis, echoing the findings of Shehzad et al. (2021). The abrupt disruptions in the stock and oil markets emphasised the destabilising influence of crises like COVID-19, worsening investor fears of financial loss (Chen et al., 2020).

This study marks a significant contribution to the financial literature, offering a comprehensive analysis of volatility across major financial assets and markets during the COVID-19 pandemic. The findings raise pertinent questions about the pandemic's differential impact on financial markets and underscore the challenges of predicting its long-term consequences. The cryptocurrency market, in particular, witnessed substantial upheaval, with Bitcoin experiencing pronounced volatility trends and persistence during the crisis.

The surge in Bitcoin volatility can be attributed in part to irrational investor behaviour, fueling speculation and worsening market instability. Such speculative bubbles can be likened to viruses, infecting market sentiment and precipitating tumultuous outcomes. As markets navigate the aftermath of the pandemic, understanding these dynamics will be crucial for informing resilient financial strategies and mitigating future crises.

20. Conclusion

Volatility emerged as a hallmark of financial returns during this period, prompting researchers to employ sophisticated modelling techniques like the GARCH family models to unravel the intricacies of market dynamics. Through meticulous investigation, nuanced patterns in market volatility across various financial assets were unveiled, with models such as the exponential GARCH and GJR-GARCH shedding light on their efficacy in capturing volatility dynamics amid crises.

Despite the heterogeneous responses of financial markets to the pandemic, the pervasive uncertainty it engendered remained a common thread. While certain assets exhibited insignificant asymmetric effects, others, like Crude Oil, experienced significant positive asymmetric effects, magnifying investor apprehensions about financial loss. The disruptions witnessed in the stock and oil markets underscored the destabilising influence of crises like COVID-19, further emphasising the importance of understanding and mitigating their impact on financial stability.

This study represents a significant contribution to the financial literature by providing a comprehensive analysis of market volatility across major financial assets during the COVID-19 pandemic. The findings underscore the challenges inherent in predicting the long-term consequences of such crises and emphasise the need for resilient financial strategies to navigate future uncertainties. As markets continue to grapple with the aftermath of the pandemic, a nuanced understanding of volatility dynamics will be essential for fostering stability and resilience despite future crises.

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