# CRYPTOCURRENCY AS A FINANCIAL ASSET : ITS VOLATILITY AND LINKAGES WITH MACROECONOMY

*By : Shweta Goel*

*Under the Supervision of Prof. Pravakar Sahoo*[1]

## Abstract

Cryptocurrency plays a crucial role in the economy despite its inherent volatility. While a lot of study has empirically examined the efficiency of the Crypto Market from the perspective of operational efficiency and productivity, very few studies have looked at the informational efficiency of the Crypto Market.This work aims to study the price volatility behavior of three important cryptocurrencies i.e. Ether, USD Coin (*which is linked to USD*) & DGX Gold token(from here onwards referred as DIGIX and *is backed by gold*) and hence discover the presence of informational efficiency.

Further, we examine if there exists any linkages between cryptocurrencies and macroeconomy i.e. Monetary policy (US Fed rate), Fiscal policy (US Fiscal Balance) and Financial market(S&P 500 Index) have any impact on the Crypto market i.e. on the value of the CMC Crypto 200 Index. For the empirical evaluation we have taken the daily closing prices of Ether, Digix & USDC for the period 09$^{th}$ Oct, 2018 to 24$^{th}$ March 2022, consisting of nearly 1263 observations. For the empirical investigation into the volatility, we have used the GARCH model. The price movements exhibit the stylized facts of financial time series such as non-normal distribution, volatility clustering and volatility persistence. The macroeconomic analysis of price movements revealed that all the three currencies have the existence of volatility persistence which is explosive in all the three cases. Ether has the least volatility persistence and USDC has maximum and that makes USDC the most informationally inefficient currency. The findings of Bivariate regressions suggest that the Stock market and Monetary Policy have a negative & significant impact on the Crypto market. However, no impact of Fiscal Policy has been observed on the Crypto market.

---

[1] Thanking Prof. Arup Mitra and Ms. Sonali Chaddha for their guidance and help
Officer Trainee, Indian Economic Service, 2022, Contact details - 9958093239, goelshweta11@gmail.com

# Introduction

The changes in the price of an asset in the securities market is referred to as volatility. It could either be healthy or extreme, in the former case there are steady increases or decreases in price within a general range, while in the latter it can be extreme, with sudden price movements in either direction.

Without going into the empirical tests for volatility, one could glance through historical price charts to see that skyrocketing peaks and depressive troughs occur at a quicker and more extreme pace in crypto prices compared to prices of assets in mainstream markets. In 2016, the price of bitcoin rose by 125% and in 2017 the price rose again, this time by more than 2,000%. Following the 2017 peak that saw it hit new all-time highs, bitcoin’s price receded once more. In 2021, bitcoin continued to set new all-time highs, more than tripling the peak price bitcoin achieved during the 2017 bull run, but crashed again in 2022 by more than 70%. News developments and speculation are responsible for fueling price swings in crypto and mainstream markets alike. But their effect is exaggerated in crypto markets as they have less liquidity than traditional financial markets — a result of crypto markets lacking a robust ecosystem of institutional investors and large trading firms. Heightened volatility and a lack of liquidity can create a dangerous combination because both feed off of each other. Other than bitcoin, most other cryptocurrencies also lack established and widely adopted derivatives markets.

### 1. Volatility and Efficiency

The Efficient Market Hypothesis is built on the assumption that prices reflect all the available information. Efficiency has further been classified into strong, semi-strong, and weak forms of efficiency. An efficient cryptocurrency market is valuable for the following four reasons:

- It promotes market participation among investors and aids in the expansion of the secondary market. Their belief that Cryptos are fairly valued is crucial to this encouragement. Instead, if they believe that cryptos are overvalued, they will often refrain from investing out of concern that they won't get a fair price when they decide to sell. The availability of money will also be restricted and a company's potential to grow if stocks are priced incorrectly.
- It gives business managers the right message. A successful market represents crypto holder wealth maximization through crypto prices, therefore sound financial judgement depends on proper crypto

pricing. A manager must be sure that the significance of the strategy is appropriately transmitted to crypto holders and management through an increase in crypto price in order to operationalize a wealth-maximizing plan. The managers are motivated to pursue greater wealth-maximizing methods by the feedback they receive from the market.

- By serving as a mediator and directing depositors' money to businesses that use it for projects, it aids in resource allocation.
- Liquidity grows as a result, institutional constraints are lifted, and the quality of market information is improved.

Another important concept linked with efficiency is volatility, or in our case the volatility clustering. Volatility clustering/persistence is defined by **Mandelbrot (1963)** , "*large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes*." Now we can link both the concept of efficiency and volatility clustering as follows. We conjecture that if there is volatility persistence that is displayed by the underlying security, then it would mean that the security prices are not following a random walk. If it doesn't follow a random walk, then one could naturally assume it to be informationally inefficient. In other words, a steady increase in the volatility can be perceived as the inability of the price to capture new information, since irrational investor behaviour appears to be the cause of this volatility (**Bulkley & Harris, 1997**). This rise in volatility causes an asset to be mispriced and would lead to misallocation of resources. (**Karmaka, 2006; Hameed 2009**)

In order to investigate this linkage we have taken the price volatility persistence of three types of cryptocurrencies, Ether, USDC & Digix and then compared them on the basis of presence of informational efficiency. Further, we also investigate the impact of the Financial market, Monetary policy and Fiscal policy on the Crypto Market.

## 2. Research objective:

The study aims to:

1. To test the price volatility nature of three important cryptocurrency i.e. Ether, USD Coin (linked to USD) & Digix (backed by Gold) using the GARCH models and then comparing the three cryptocurrencies on the basis of informational efficiency.
2. To check if there exists any linkages between crypto market and macroeconomy i.e. Fiscal policy, represented by Fiscal Balance, Monetary policy, represented by USA Fed rate and Capital market,

represented by S&P 500 Index have any impact on CMC Crypto 200 Index.

## 3. Historical background

Digital cash, which used cryptography to protect and authenticate transactions, was created by the eminent American cryptographer David Chaum in 1980. Chaum also popularised cryptocurrencies in 1989. A genuinely decentralised digital money might be produced thanks to cryptographic protocols and software developed in the early 1990s.

Satoshi Nakamoto advocated developing a digital currency system without the need for third-party trust in his paper Bitcoin: A Peer-to-Peer Electronic Cash System, which was released in October 2008. The cryptocurrency revolution was launched by Satoshi Nakamoto's paper.

## 4. The Launch of Bitcoin – 2009

In 2009, the same year it was made available as open-source software, Satoshi Nakamoto created the Bitcoin protocol. People who want to transmit money across borders unhindered by banks or governments are becoming more and more interested in it. Despite its quick increase in value, some people are still unsure about what to do with their Bitcoins.

On January 12th, 2009, Nakamoto and Hal Finney carried out the first Bitcoin transaction. Only when someone spent 10,000 Bitcoins to have two pizzas delivered by Papa John's in February of the following year did someone recognise the possibilities of this new technology. Millions have passed since that transaction.

In the beginning of 2010, Bitcoin was the only cryptocurrency available. It cost only a few cents. New digital currencies were introduced during the following few years, and their values fluctuate along with that of Bitcoin. Many people lost hope in cryptocurrencies as investments during this period of turmoil. The cryptocurrency sector started to experience remarkable growth in late 2017. Currently, there are over 8,500 cryptocurrencies in circulation, with a market value of over $2 trillion. This represents 18% of the world's gold reserves. The market for cryptocurrencies is expected to grow to $4.94 billion by 2030 and $2.73 billion by 2025.

## 5. Cryptocurrency

In a nutshell, cryptocurrency, usually referred to as crypto-currency, is any kind of virtual or digital currency that uses cryptography to safeguard transactions. Cryptocurrencies employ a decentralised mechanism to track transactions and create new units rather than being governed or issued by a centralised organisation. Payments made using cryptocurrencies only exist as digital entries in an online database that detail specific transactions. Payments made with cryptocurrencies support the upkeep of a public log of transactions instead of carrying or exchanging physical cash in the real world. Digital wallets are where cryptocurrency is kept.

The blockchain acts as the cryptocurrency's ledger, providing a record of all updates and transactions made by users. The technique of "mining," which uses computer power to solve challenging mathematical problems to produce coins, is how cryptocurrencies are made. Users can buy the currency from a broker, then store it in encrypted wallets and use it to make purchases.

Cryptocurrencies are not just an investment; they can also be used to pay for products and services. It can be used as a form of payment at many restaurants, on flights, and in apps. At the moment, people are using crypto projects for minting NFTs (non fungible tokens). It is also being utilised in DeFi (decentralised finance), which is essentially a bank that does banking-related operations like lending money, providing insurance, and other tasks in a decentralised peer-to-peer lending system. Users can trade cryptocurrencies on exchanges where their businesses accept them as payment for services in nations where they are legal to do so. Cryptocurrencies are used to finance terrorism and money laundering in nations where they are prohibited.

After the brief historical development of cryptocurrency let us build the discussion on the currencies that we have taken for our analysis.

### 5.1. Ethereum

After Bitcoin, Ethereum (ETH) is the second-most popular cryptocurrency (rank 2). With a market capitalization of more than 17% of the $1.2 trillion global cryptocurrency market, it was launched by Vitalik Buterin in 2015. It holds 16 percent market share. Ethereum is meant to be much more than just a means of commerce or a store of currency. Instead, Ethereum uses blockchain technology to operate as a decentralised open source computing network, and it has its own currency called Ether. Blockchain transactions are protected and verified by cryptography.

Ethereum has following characteristics:

- On the Ethereum blockchain, which is the blockchain where Ether is stored and traded, thousands of financial and gaming applications operate. According to Ethereum, a worldwide, decentralised platform for financial transactions and novel applications.
- On the Ethereum network, the transactions are processed and stored.
- The Ethereum network may host decentralised applications in addition to storing data and operating them. Hosting decentralised

apps on Ethereum is an alternative to doing it on Google or Amazon servers, where one company controls the data.

- Smart contracts, also known as self-executing contracts, are more common in Ethereum. The delivery of products or services is agreed upon by the parties, just like in any contract. No attorneys are required because the parties coded the agreement on the Ethereum blockchain themselves. When the terms of the contract are fulfilled, it self-executes and delivers Ether to the right party.

### 5.2. Digix gold token

In March 2018, Digix DAO released DGX, a cryptocurrency coin whose value is linked to the price of gold through redemption into actual gold. A Proof of Asset system is used to create DGX coins, each of which represents one gramme of gold (PoA). The certification is kept on the Ethereum blockchain, and the PoA makes sure that enough gold has been purchased and held against each DGX. The third party auditor verifies the gold's quality and quantity, the vendor provides the gold, and the vault handles the Proof of Asset. DGXs are issued in relation to PoA cards that provide evidence of the stored gold, such as the card's timestamp, the gold bar's serial number, audit records, and chain of custody digital signatures.

The top 1,000 cryptocurrencies by market capitalization did not include DGX.

### 5.3. USD coin

With a market worth of $73 billion, USD Coin is the second-largest stablecoin behind Tether (USDT) and the fourth most widely used cryptocurrency, with a market share of 6%. A regulated stablecoin based on blockchain technology called USD Coin was developed. A stablecoin called USD Coin has a value tied to the US dollar.

Since USD Coin is a stablecoin, one USDC should always be equivalent to one dollar. The second-largest stablecoin at the moment, behind Tether, is USD Coin.

Stablecoins are digital currencies whose value is linked to another asset, such as a fiat currency, a commodity, or even another digital currency like USD Coin, which strives to maintain a one-to-one peg with the dollar.

A stablecoin, like USDC, differentiates from coins with volatile values like Bitcoin (BTC) or Ethereum (ETH). Instead of being an asset that could possibly increase in value over time, USDC acts as a reliable store of value.

## 6. Indices for Bivariate Regression Analysis

### 6.1 CMC Crypto 200 Index

This Coinmarketcap index tracks the changes in price of a portfolio of the top 200 cryptocurrencies according to market capitalization. This index is Published in USD.

### 6.2 S&P 500 Index

The Standard and Poor's 500, sometimes known as the S&P 500, is an index used to measure the performance of 500 significant firms that are listed on American stock exchanges..

# Literature review

In recent years, there have been an increasing number of empirical studies in the financial literature that analyse cryptocurrencies in-depth. Since cryptocurrencies must contend with accusations of potential unlawful usage and inexperienced exchange platforms, among other things, Corbet et al. (2019) do a thorough evaluation of the available studies in the sector, suggesting that they are trusted investment assets with legitimate value. summarises the key findings of earlier studies on the existence of return and volatility spillovers in the bitcoin market. Kyriazis (2019)

With the exception of gold, Kurka (2019) finds little link between Bitcoin and other traditional asset classes. Smales (2019), on the other hand, contends that there is no correlation between Bitcoin returns and those of other asset classes and that cryptocurrencies shouldn't be viewed as a safe haven until the market for them has stabilised.

During the first and second waves of the COVID-19 pandemic crisis, Umar et al. (2021c) look into the dynamic return and volatility connectivity between three cryptocurrencies (Bitcoin, Ethereum, and Ripple) and three fiat currencies (the euro, GBP, and Chinese yuan).

The relationship between cryptocurrencies and other asset classes has already been analysed using a variety of methodological approaches, including VAR models (Baço et al., 2018 and Conlon and McGee, 2020), GARCH models (Corbet et al., 2020b), and VAR-GARCH models (Symitsi and Chalvatzis, 2019), Numerous studies have been done on Bitcoin, but very few have been done on other currencies, especially stablecoins. The aim of this research is to examine the price volatility of other significant cryptocurrencies including Ether, USD Coin, and DGX. We have made an effort to investigate how cryptocurrencies and the macroeconomy are related.

# Data

The information utilised in this work was gathered from a dependable source. Historical daily data for ETHER, DIGIX, and USDC was obtained from Coindesk, from October 9, 2018, to March 24, 2022, roughly 1263 observations, . For testing price volatility, closing prices have been taken into account.

S&P 500 Index data is gathered from yahoo.finance for the same time period and is used as a stock market indicator.

Fed Rates have been used as a measure of monetary policy, while Fiscal Balance (Deficit/Surplus) has been used as a measure of fiscal policy. For the time period from October 2018 to March 2022, monthly data for both variables were gathered from the FRED website.

We believe that it helps create information and resources that are valuable to practitioners and scholars who research and form cryptocurrency markets in the future

# Methodology

## 1. Unit root Test (Augmented Dickey Fuller Test)

In time series modelling it is needed to make our variables stationary for valid inferences. In order to be stationary, a series must have,

- Constant Variance.
- Constant Mean.
- Same Covariance given the same lag length.

Generally, the available is non-stationary, implying changes in mean and variance with time. If an analysis is done with non-stationary data, the results might get skewed or we may end up achieving spurious results.

The series has unit root, which implies non-stationarity can be found out by the following tests:

- Phillip – Perron test
- KPSS test
- Dickey-Fuller Test
- Augmented Dickey Fuller Test

The first three tests assume a null hypothesis as non-stationarity and the KPSS test assumes stationarity. We used the "Augmented Dickey Fuller test (ADF test)" for checking stationarity. To understand the Augmented Dickey Fuller test, we need to understand the "Dickey Fuller test".

The equation is considered as

$$Y_t = \alpha + \beta Y_{t-1} + u_t,$$

Here the term ut is the error term which has zero mean, constant variance and is also uncorrelated. This kind of disturbance is called white noise. Here we assume a long period of study, then we have,

$$Y_t = \alpha(1 + \beta + \beta^2 + \ldots) + (u_t + \beta u_{t-1} + \beta u_{t-2})$$

***Mean of Yt :***

$$E(Y_t = \alpha(1 + \beta + \beta^{2+\cdots}))$$

This will be valid only when β<1

$$E(Y_t) = \mu = \alpha/(1 - \beta)$$

Therefore, the mean, μ is constant in the series Yt at all the periods.

Variance of Yt :

$$Var(Y_t) = E[Y_{t-\mu}2\ ] = \sigma^2 Y = \sigma^2/(1 - \beta^2)$$

This series Yt has a constant variance which is not dependent on time period. Autocovariance in the series Yt We calculate the autocovariance, which is the covariance of Y with its lagged terms, which is

$$\gamma_t = E[(Y_{t-\mu})(Y_{t-1-\mu})] = \beta^s \sigma^2_y$$

in general form $\gamma_t = \beta^S \sigma^2{}_y$, $S = 0,1,2,3..$

It is dependent on length of the lags, not time period(t).

Considering an auto regressive process at order 1,

$$Y_t = \mu + \beta Y_{t-1} + e_t$$

Here the terms μ as well as β are considered as parameters and the term et is considered as white noise. If the parameter β lies between -1 to +1 then the process is not having unit root, if the value of the parameter β is 1 then the series is at non-stationarity. The test is carried out by reducing Yt−1 from both sides of the equation, which results as follows,

$$Y_t = \mu + \gamma Y_{t-1} + e_t$$

Where Y = β - 1 and the null hypothesis and the alternate hypothesis are:

H0: $\gamma = 0$, which implies $\beta = 1$

H1: $\gamma < 0$, which implies β ¡ 1

To check the significance of the results we use t-test, where we accept the null hypothesis if the critical value is greater than calculated value implying unit root and reject if vice-versa happens. We assume there is no autocorrelation in this test.

ADF test is used for higher order process by assuming ARp process which is done by adding lagged difference terms of the dependent variable,

$$\Delta Y_t = \mu + \gamma Y_{t-1} + \delta_1 \Delta Y_{t-1} + \ldots + \delta_{p-1} \Delta Y_{t-p-1} + e_t$$

The null and the alternative hypothesis states:

H0 : $\gamma = 0$ and H1: $\gamma < 0$

Unit root is checked by employing t-test. The acceptance of null hypothesis states the presence of unit root implying the series is non-stationary and vice-versa for stationary series.

## 2. Assessment of Generalised Auto-Regressive conditional heteroskedasticity(ARCH) Effects

To apply GARCH models to the Ether, Digix and Usdc price series, the presence of stationarity and ARCH effects in the residual price series are tested. The White's test is used to test for the presence of ARCH effects in the data.

## 3. Symmetric Garch Model

Since there is heteroscedasticity in the price of cryptocurrencies which implies variance is not constant given the data and time period. So, an OLS estimation is not possible, as its basic assumption is homoscedasticity. In order to capture the high volatility in the financial time series data more sophisticated models like GARCH framework came to existence to understand the heteroscedasticity in the data.

Even though the ARCH model developed by Engle (1982) can be done with ease but it does not decide the volatility process entirely by itself, it requires us to specify the distribution at a given point in time. Whereas the GARCH model proposed by Tim Bollerslev (1986) does not require volatility at a particular point of time, volatility itself is stochastic.

The generalised method of ARCH is called GARCH. Therefore, we have used the GARCH framework to check the conditional variance. For using the GARCH framework for our study we have done ARCH-White heteroscedasticity test. This test is used to check the ARCH effect on the residual data. Akaike Information Criteria (AIC) is used to identify the appropriate lag length. Bollerslev(1986) GARCH (p,q) model has been incorporated in our study,

$$h_t = \alpha_0 + \Sigma^{p}_{t-1} \alpha_i \varepsilon^2_{t-1} + \Sigma^{q}_{j-1} B_j h_{t-j}$$

Above equations give the formula for a conditional mean and conditional variance. The lag length for the ARCH term is 'p' and for the GARCH term is 'q'.

The conditional variance equation is as follows:

$$h_t = \alpha_0 + \alpha_1 \varepsilon^2_{t-1} + \beta_1 h_{t-1}$$

## 4. The GJR GARCH model

The other commonly used model to incorporate asymmetric volatility was developed by Glosten, Jagannathan & Runkle (1993). The model is called GJR-GARCH and an advantage with the model is that the variance is directly modeled and does not use the natural logarithm like the EGARCH model. This means that the GJR-GARCH is simpler to implement in practice (Hayashi, 2000). Studies that have applied several GARCH models have deemed the GJR-GARCH the most sufficient in forecasting the volatility and VaR estimation (Su & Chen, 2009; Liu & Hung, 2010).

The GJR-GARCH(1,1) model is stated in the equation below (Asgharian, 2016):

$$\boldsymbol{\sigma} t^2 = \boldsymbol{\omega} + \boldsymbol{\alpha_1 \eta_{t-1}}^2 + \boldsymbol{\alpha_2 I_{t-1} \eta_{t-1}}^2 + \boldsymbol{\beta \sigma_{t-1}}^2$$

Explanation of the variables used in the GRJ-GARCH model:

$\boldsymbol{\sigma} t^2$ : is the conditional forecasted variance.

$\boldsymbol{\omega}$: is the intercept for the variance.
$\boldsymbol{\alpha_1 \eta_{t-1}}^2$: is the variance that depends on previous lag error terms.

$\boldsymbol{\alpha_2}$: is the scale of the asymmetric volatility.

$\boldsymbol{I_{t-1}}$: is a dummy variable.

$\boldsymbol{\beta}$: is the coefficient for yesterday's forecasted variance.

$\boldsymbol{\sigma_{t-1}}^2$ : yesterday's forecasted variance.

$It-1$ is a dummy variable that is only activated if the previous shock is negative ($\eta t-1 < 0$) , allowing the GJR-GARCH to take the leverage effect into consideration (Glosten et al, 1993; Asgharian, 2016).

$$I_{t-1} = \begin{cases} 1 \text{ if } \eta_{t-1} < 0 \\ 0 \text{ otherwise} \end{cases}$$

Equation shows that in the case of $\alpha 2 = 0$ the GJR-GARCH becomes a regular symmetric GARCH(1,1) model. A negative shock is captured by ($\alpha 1 + \alpha 2$) and a positive shock is captured by $\alpha 1$ (Asgharian, 2016). The sign of the leverage effect is the opposite compared to the EGARCH (Dutta, 2014).

If $\boldsymbol{\alpha_2} = 0$, symmetry i.e. no asymmetric volatility.

If $\alpha_2$ > 0 negative shocks will increase the volatility more than positive shocks.

If $\alpha_2$ < 0 positive shocks increase the volatility more than negative shock.

## 5. Bivariate Regression

To check the impact and linkages of Real world macroeconomics policies with the Crypto Market, bivariate regression has been used. We have taken three variables to check their impact on the Value of CMC Crypto 200 Index. Hence Value on CMC Crypto 200 is dependent variable and rest of three are independent variables and bivariate regression has been used. Three independent variables representing real world macroeconomic policies are Fiscal Balance(Deficit/Surplus), Monetary policy Fed rates, and S&P 500 Index(Financial market).

When describing the relationship between a dependent variable and an independent variable, linear regression (sometimes referred to as bivariate regression) specifically makes the assumption that the dependent variable affects the independent variable, not the other way around.

In the sample, a two-variable simple linear regression equation has the following form:

yi=b0+b1xi+ei

where b1 is the sample estimate of the slope of the regression line with respect to years of education and b0 is the sample estimate for the vertical intercept of the regression line.

The error term ei is residual in regression.

# EMPIRICAL ANALYSIS

In this section we present the empirical results of our study which includes time series plot, stationarity in the series and family of GARCH models for checking the volatility persistence, asymmetry and leverage effect in the prices of three cryptocurrencies and simple regression results.

## 1. Descriptive Analysis

In order to understand the characteristics of the Ether, Usdc & Digix series we calculated the descriptive measures and the results are provided in the table.

*Table : Descriptive Statistics*

| | Price_Ether | Price_Usdc | Price_Digix |
|---|---|---|---|
| Mean | 1147.542 | 1.002309 | 50.23547 |
| Median | 279.1139 | 1.000050 | 49.51838 |
| Maximum | 4812.087 | 1.056577 | 127.8229 |
| Minimum | 84.24895 | 0.982591 | 25.50561 |
| Std. Dev. | 1352.822 | 0.006575 | 9.839763 |
| Skewness | 1.080254 | 2.592302 | 1.475657 |
| Kurtosis | 2.710137 | 12.78622 | 13.32022 |
| Jarque-Bera | 250.0645 | 6454.472 | 6063.304 |
| Probability | 0.000000 | 0.00000 | 0.000000 |
| Sum | 1449346 | 1265.917 | 63447.40 |
| Sum Sq. Dev. | 2.31E+09 | 0.054561 | 122188.0 |
| Observations | 1263 | 1263 | 1263 |

*Source : Based on Author's calculation*

On the side of skewness, we can observe that it is positive in all three Cryptocurrencies's prices, so it can be considered that they have a similar behaviour i.e. not symmetrically distributed

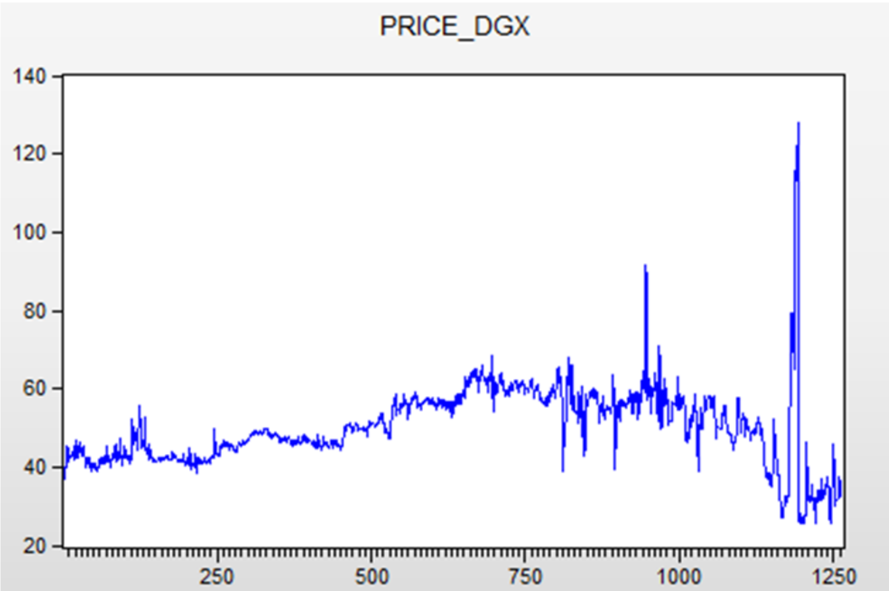
The kurtosis coefficient is a measure of pointing that indicates the degree of concentration of the data around the mean. As the value is 12.78622 for Usdc & 13.32022 for Digix which is greater than 3 we can say that it has a fat tail distribution except Ether. This fat tail distribution is common in financial time series data which is leptokurtic.

The normality analysis measured through the Jarque-Bera (JB) test shows that all the log returns of the main cryptocurrencies reject the null hypothesis, i.e., the variables do not follow a normal distribution (the values are excessively high). Hence it is clear that the return series follows a non normal distribution.

# 2. Time-Series Plot

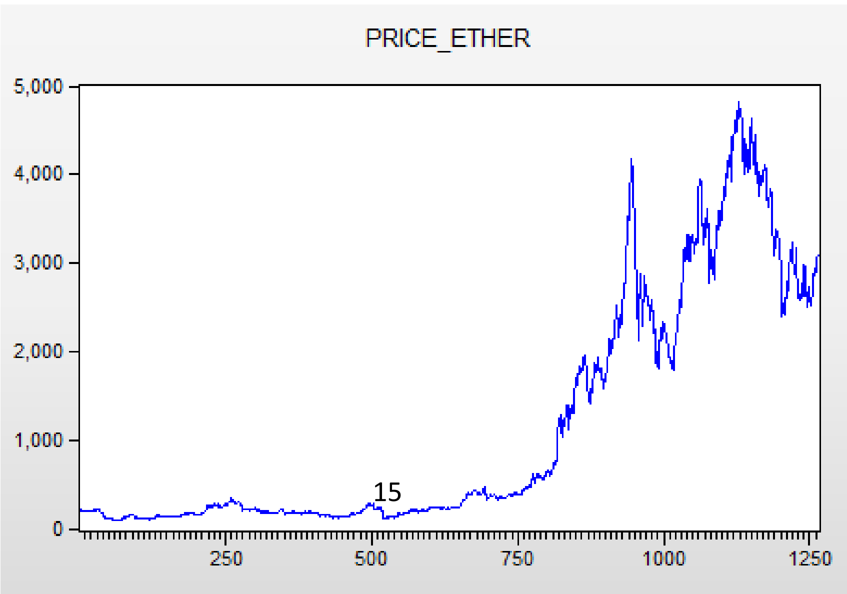
From the time series plot of the Ether, Usdc & Digix from the time period 9$^{th}$ oct, 2018 to 30$^{th}$ march, 2022, we can infer that the phenomenon of volatility clustering is present. Volatility clustering is a phenomenon where an instance of low prices is followed by a period of low prices and an instance of high prices is followed by a period of high prices. The presence of volatility clustering acts as evidence for us to use GARCH models for modelling volatility of cryptocurrencies.

*Time series plot : DGX's Price*

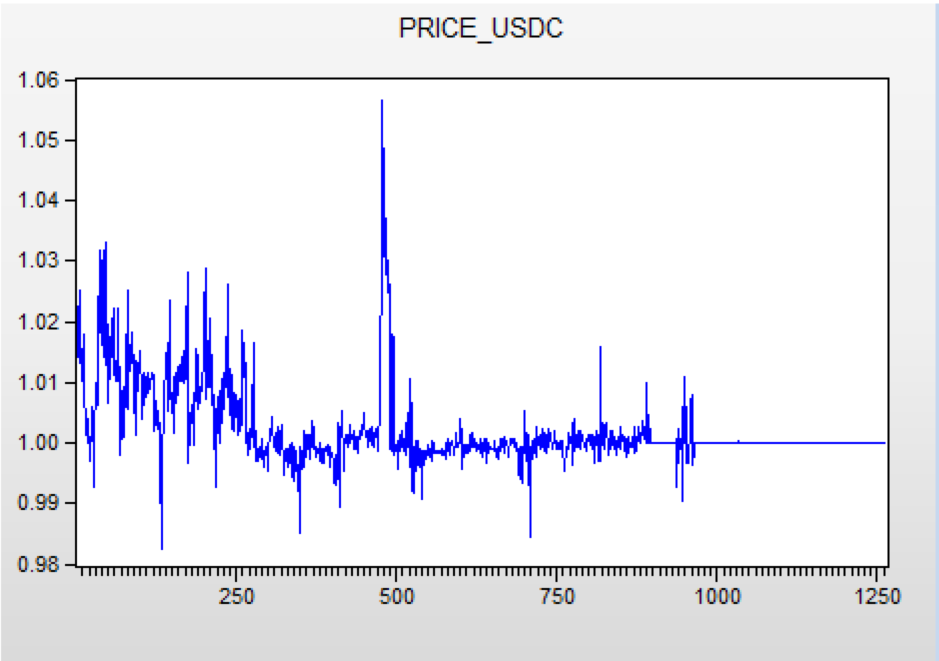



*T*

*Time Series Plot : Ether's Price*



*Time Series Plot : USDC's Price*




*Source : Based on Author's calculation*

# 3. Results of Stationarity test

Stationarity means the statistical properties of a process of time series do not change over time. The Augmented Dickey-Fuller (ADF) test is conducted for checking the stationarity of Ether, Usdc & Digix.The results of the ADF test are as follows:

*Table : ADF Test Results*

| | t-stat. | Prob. | order |
|---|---|---|---|
| Ether | -21.3498 | 0.000 | I(1) |
| Usdc | -7.9883 | 0.000 | I(0) |
| Digix | -5.276891 | 0.000 | I(0) |

*Source : Based on Author's calculation*

From the above table, it is observed that the series of prices of Ether is stationary at first difference whereas the series of Prices of USDC & DGX are stationary at levels only and they all are statistically significant at 1% level.

# 4. Estimation of GARCH models

In this section we employ various GARCH models i.e. symmetric as well as asymmetric models to understand the volatility behaviour of prices of Ether, Usdc & Digix.

## • Results of GARCH (1, 1) model

For checking the volatility persistence in the prices of these cryptocurrencies i.e. Ether, Digix and Usdc and we have used the GARCH model and using the Akaike Information Criteria (AIC) and we found that the GARCH(1,1) framework is a good fit for the returns series considered in this study. The Symmetric GARCH is generally represented as:

$$\sigma^2{}_t = \alpha_0 + \alpha_1\varepsilon^2{}_{t-1} + \beta_1\sigma^2{}_{t-1}$$

The results of the Symmetric GARCH is represented in the following tables:

*Table : Results of Garch(1,1) for ETHER*

| Variables | Symbols | Coefficients | Z-statistic | Probability |
|---|---|---|---|---|
| Intercept | $\alpha_0$ | 3.250059 | 6.918669 | 0.0000 |
| Arch | $\alpha_1$ | 0.206714 | 12.46322 | 0.0000 |
| Garch | $\beta_1$ | 0.819120 | 62.38921 | 0.0000 |

*Source : Based on Author's Calculation*

From the above table, we can observe the phenomenon of volatility persistence is present in Ether as the sum of the coefficients of two terms, α1 which represents the ARCH term and β1 which represents the GARCH term is **1.025834**. The sum being 1.025834 acts as an evidence that the existence of volatility persistence is explosive in nature as the sum is greater than 1.

*Table : Results of Garch(1,1) for USDC*

| Variables | Symbols | Coefficients | Z-statistic | Probability |
|---|---|---|---|---|
| Intercept | $\alpha_0$ | 7.11E-10 | 0.420297 | 0.6743 |
| Arch | $\alpha_1$ | 0.485941 | 36.68221 | 0.0000 |
| Garch | $\beta_1$ | 0.657738 | 95.30697 | 0.0000 |

*Source : Based on Author's Calculation*

From the above table, we can observe that the phenomenon of volatility persistence is present in USDC as the sum of the coefficients of two terms, α1 which represents the ARCH term and β1 which represents the GARCH term is **1.143679.** The sum being 1.143679 acts as an evidence that the existence of volatility persistence is explosive as the sum is greater than 1.

*Table : Results of Garch(1,1) for DIGIX*

| Variables | Symbols | Coefficients | Z-statistic | Probability |
|---|---|---|---|---|
| Intercept | $\alpha_0$ | -0.002895 | -0.848035 | 0.3964 |
| Arch | $\alpha_1$ | 0.148348 | 20.90425 | 0.0000 |
| Garch | $\beta_1$ | 0.905054 | 216.1005 | 0.000 |

*Source : Based on Author's Calculation*

From the above table, we can observe that the phenomenon of volatility persistence is present in Digix as the sum of the coefficients of two terms, α1 which represents the ARCH term and β1 which represents the GARCH term is **1.053402**. The sum being 1.053402 acts as an evidence that the existence of volatility persistence is explosive as the sum is greater than 1.

# 5. Results of GJR GARCH models

The GJR GARCH model is used for checking the leverage effect on returns. Leverage effect is identified by negative correlation between the asset's prices and asset's volatility. For the leverage effect, the term should be $\gamma > 0$ and statistically significant in the model.

GJR GARCH model is represented as follows:

$$\sigma^2{}_t = \alpha_0 + \alpha_1 u^2{}_{t-1} + \beta\sigma^2{}_{t-1} + \gamma u^2{}_{t-1} I_{t-1}$$

*Table : Results of GJR Garch(1,1) for* ETHER

| Variables | Coefficients | Z-statistic | Probability |
|---|---|---|---|
| Intercept | 1.900432 | 5.191187 | 0.0000 |
| Arch | 0.205398 | 9.979305 | 0.0000 |
| Garch | 0.885234 | 79.47768 | 0.0000 |
| Tarch | -0.162298 | -8.688551 | 0.0000 |

*Source : Based on Author's Calculation*

From the table, we can infer that there is leverage effect as the term $\gamma$ is negative and statistically significant implying leverage effect which implies that the impact of positive shocks on volatility is higher than the negative shocks on the price volatility of Ether.

*Table : Results of GJR Garch(1,1) for USDC*

| Variables | Coefficients | Z-statistic | Probability |
|---|---|---|---|
| Intercept | 1.06E-08 | 2.034136 | 0.0419 |
| Arch | 0.335269 | 9.372824 | 0.0000 |
| Garch | 0.724693 | 40.82290 | 0.0000 |
| Tarch | 0.047917 | 0.878937 | 0.3794 |

*Source : Based on Author's Calculation*

From the table, we can infer that there is no leverage effect as the term $\gamma$ is positive but statistically insignificant implying no leverage effect.

*Table : Results of GJR Garch(1,1) for DIGIX*

| Variables | Coefficients | Z-statistic | Probability |
|---|---|---|---|
| Intercept | -0.003928 | -1.065683 | 0.2866 |
| Arch | 0.137076 | 18.16150 | 0.0000 |
| Garch | 0.898828 | 172.2925 | 0.0000 |
| Tarch | 0.044005 | 2.384827 | 0.0171 |

*Source : Based on Author's Calculation*

From the table, we can infer that there is leverage effect as the term γ is positive and statistically significant implying leverage effect which implies the price of Digix is negatively correlated to their volatility. It means that negative shocks have a greater impact than the positive shocks on the price volatility of Digix.

We can observe from the above results that leverage effect is present in case of two currencies i.e. Ether & DGX. However it is positive in one case and negative in another one, implying that in case of Ether, positive shocks have greater impact on its price volatility but in case of DGX, negative shocks have greater impact on the price volatility. Additionally, no Leverage effect was observed in the case of USDC.

We can conclude from the GARCH analysis that maximum volatility persistence is present in USD Coin, a cryptocurrency which is linked to USD. Ether has the least volatility persistence and DGX lies in between two currencies in terms of volatility persistence. Ether was launched in 2015 and has been present in the economy for a long time and that can be one reason for the relative stability in Ether as compared to other two as they were launched in 2018, quite recently. However, in case of all the three currencies, volatility persistence is explosive as in all the cases summation of arch and garch coefficients are greater than one.

Results depicted that USDC is the most informationally inefficient cryptocurrency among the three cryptocurrencies i.e. it has the least capacity to capture new information.A group of American companies, including the bitcoin miner Bitmain, the payments company Circle, and the cryptocurrency exchange Coinbase, hold USDC. These 1:1 ratios do not happen by accident. They rely on stablecoin providers maintaining financial asset reserves equal to the value of the stable coins that are in use, which fluctuate based on investor demand and supply. The providers claim to have reserves equal to 100% of the value of their stablecoins, although that claim is not entirely true.USDC holds 61% of its reserves in cash and equivalents as of May 2021, short of 100%. A large part of the assets of both operations are based on commercial papers, which is a form of short-term company debt. This is not cash equivalent and poses a solvency risk in the event of a sudden collapse in the value of these assets.This can be one reason why USD Coin has the maximum volatility persistence and that makes it most informationally inefficient among the three cryptocurrencies. This shows that stablecoins are actually not stable as such. For example, the recent collapse of Terra USD.

# 6. Results of Bivariate regression

## 6.1 Regression of S&P 500 on CMC Crypto 200 Index

Knowing the relationships of the cryptocurrency market with the stock market will be very useful to manage investors' portfolios and how many portions of their investment money will be allocated to cryptocurrency for their secure and profitable investment plan.

Equation is as follows :

CMC_Crypto_200 = b1 + b2(S&P500)

*Table : Regression results*

| Variables | Coefficients | Std. Error | T - statistic | Probability |
|---|---|---|---|---|
| C | 748.3745 | 18.29976 | 40.89532 | 0.0000 |
| S&P500 | -0.128451 | 0.007221 | -17.78931 | 0.0000 |

*Source : Based on Author's Calculation*

b2 =-0.128451, which shows that if the value of S&P 500 Index is increased by one unit, then it will decrease the value of CMC Crypto 200 Index by -0.128451 units.The findings suggest that there is a negative time-varying relationship between these two markets since the COVID-19 occurrence.

These two markets are alternative Investment options for people. If people start investing in stock markets, then demand for cryptocurrencies will decline and thereby decrease the Price of crypto. Hence they represent a negative relation with each other. However, sometimes they behave in the same direction as well in unexceptional circumstances such as when overall sentiments of the market are low, then demand will decrease in both the market and it will lower the value of both Indices.

## 6.2 Regression of USA Fed policy rates on CMC Crypto Price Index

Monetary policy shocks have been studied in numerous works through various topics, but a broad study incorporating various cryptocurrencies has been missing. Due to the economic fundamentals, as interest rates rise, returns on risk-free assets increase, which will deter investors from other investments, including cryptocurrencies. This reduction in demand should be visible in price and hence the return on investment.

Equation is as follows:-

CMC_Crypto_200 = b1 + b2(Fed_rate)

*Table : Regression results*

| Variables | Coefficients | Std. Error | T - statistic | Probability |
|---|---|---|---|---|
| C | 847.6107 | 73.11348 | 11..59308 | 0.0000 |
| Fed_rate | -319.0242 | 51.891109 | -6.147958 | 0.0000 |

*Source : Based on Author's Calculation*

Our results clearly reflect a negative and significant impact of the US's Fed rates (Monetary Policy) on the value of CMC Crypto 200 Index. It means that if the Fed rate increases by 1% then prices of ether decreases by 319.0242. This happens because when Govt. uses tight monetary policy, then interest rates in the economy goes up which makes investors to shift towards safer investment options. This leads to decrease in the demand of the cryptocurrencies and hence decrease in their prices as well.

## 6.3 Regression of Fiscal Balance on CMC Crypto 200 Index

In this Bivariate model, we are trying to check the impact of Fiscal policy of the US government on the cryptocurrency market. Fiscal balance(Deficit/Surplus) is taken as an indicator of Govt. Fiscal policy i.e. If the government adopts the expansionary fiscal policy then the fiscal deficit will increase and will decrease in case of contractionary fiscal policy.

Equation is as follows:-

CMC_Crypto_200 = b1 + b2Fiscal_Balance

*Table : Regression results*

| Variables | Coefficients | Std. Error | T - statistic | Probability |
|---|---|---|---|---|
| C | 532.2113 | 102.1878 | 5.208168 | 0.0000 |
| Fiscal balance | -2.32E-05 | 0.000374 | -0.02126 | 0.9508 |

*Source : Based on Author's Calculation*

In our bivariate regression model, no significant relation can be seen between Fiscal Balance and value of CMC Crypto 200 Index.The Coefficient of Fiscal Balance is negative but insignificant. One reason for the no relation could be the informationally inefficient crypto market.

# Conclusion

Cryptocurrency is considered to be an alternative investment option for investors but at the same time it is also relatively riskier than other assets because of no regulatory authority as it is completely decentralised.

In this context, this study has taken up to understand the price volatility of three different types of cryptocurrencies i.e. Ether, Usdc & Digix and also to check the impact of real world macroeconomics policies on cryptocurrency market i.e. on CMC Crypto 200 Index. For this purpose, the study has employed the symmetric and asymmetric GARCH models and Bivariate regression model.

Results of the Garch model suggest that volatility persistence exists in all the three currencies but it is least in Ether and maximum in USD Coin. In all the three cases, it is higher than 1 which means that fluctuations are explosive higher than trend. Additionally, maximum volatility persistence in USDC makes it the most informationally inefficient crypto currency as well among the three currencies(Though all three currencies are informationally inefficient).

First bivariate regression model is used to check the impact of change in value of S&P 500 on value of CMC Crypto 200 Index i.e. if there exists any kind of relationship between the stock market and crypto market. Results depicted a negative relationship between them, so, if Value of S&P 500 increases, it leads to decrease in value of CMC Crypto 200 Index & vice-versa. This means that the Stock market and Crypto market is acting as a substitute to each other as an investment option.Since stock market is well established and regulated by authorities, it is relatively stable than the crypto market which is more recent, unstable, unregularised.

Second model is used to check the impact of change in monetary policy (US Fed rates are taken as indicator) on the crypto market i.e. on the CMC Crypto 200 Index where findings suggests a negative relationship between them.It mean, if govt adopts a tight monetary policy, i.e. decides to increase the interest rates then people will start investing more in risk free asset as they become relatively profitable and move away from cryptocurrencies which is considered riskier. This led to decrease in demand of cryptocurrencies and hence decrease in prices.That is a phenomenon we have also observed recently(in 2022),when the government started adopting contractionary Monetary Policy due to rising inflation, the crypto market crashed and lost market value by more than 70%.

Third model tries to capture the effect of the government Fiscal Policy(US Fiscal balance is taken as an indicator) on the Crypto market i.e. on the CMC Crypto 200 Index. But the model found no relationship between them.

# References:

1)Corbet, S., Lucey, B., Urquhart, A., & Yarovaya, L. (2019). Cryptocurrencies as a financial asset: A systematic analysis. *International Review of Financial Analysis*, *62*, 182-199.

2)Kyriazis, N. A., Daskalou, K., Arampatzis, M., Prassa, P., & Papaioannou, E. (2019). Estimating the volatility of cryptocurrencies during bearish markets by employing GARCH models. *Heliyon*, *5*(8), e02239.

3)Kurka, J. (2019). Do cryptocurrencies and traditional asset classes influence each other?. *Finance Research Letters*, *31*, 38-46.

4)Smales, L. A. (2019). Bitcoin as a safe haven: Is it even worth considering?. *Finance Research Letters*, *30*, 385-393.

5)Aharon, D. Y., Umar, Z., & Vo, X. V. (2021). Dynamic spillovers between the term structure of interest rates, bitcoin, and safe-haven currencies. *Financial Innovation*, *7*(1), 1-25.

6)Bação, P., Duarte, A. P., Sebastião, H., & Redzepagic, S. (2018). Information transmission between cryptocurrencies: does bitcoin rule the cryptocurrency world?. *Scientific Annals of Economics and Business*, *65*(2), 97-117.

7)Conlon, T., & McGee, R. (2020). Safe haven or risky hazard? Bitcoin during the COVID-19 bear market. *Finance Research Letters*, *35*, 101607.

8)Corbet, S., Larkin, C., & Lucey, B. (2020). The contagion effects of the COVID-19 pandemic: Evidence from gold and cryptocurrencies. *Finance Research Letters*, *35*, 101554

9) Symitsi, E., & Chalvatzis, K. J. (2019). The economic value of Bitcoin: A portfolio analysis of currencies, gold, oil and stocks. Research in International Business and Finance, 48, 97-110.

10) Mandelbrot, B. B., The Variation of Certain Speculative Prices, The Journal of Business 36, No. 4, (1963), 394-419

11) Fama, E. (1970) Efficient Capital Markets: A Review of Theory and Empirical Work. The Journal of Finance 25:2, 387–417.

12) Bulkley, G., & Harris, R. D. (1997). Irrational analysts' expectations as a cause of excess volatility in stock prices. The Economic Journal, 107(441), 359-371.

13) Karmakar, M. (2006). Stock market volatility in the long run, 1961-2005. Economic and Political Weekly, 1796-1802.

14) Hameed, A., & Ashraf, H. (2009). Stock market volatility and weak-form efficiency: evidence from an emerging market. International Journal of Business and Emerging Markets, 1(3), 249-263.