VOLATILITY MODEL ANALYSIS USING EXPONENTIAL GENERALISED AUTOREGRESSIVE CONDITIONAL HETEROSKEDASTICITY (EGARCH) MODEL AND GJR GARCH ON INDIAN CRYPTOCURRENCIES

A PROJECT REPORT - I

SUBMITTED IN PARTIAL FULFILMENT OF THE

REQUIREMENTS FOR THE AWARD OF THE

DEGREE OF

BACHELOR OF

TECHNOLOGY IN

MATHEMATICS AND COMPUTING

Submitted by

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November, 2021

DECLARATION

We hereby certify that the work which is presented in the Major Project-I entitled **'VOLATILITY MODEL ANALYSIS USING EXPONENTIAL GENERALISED AUTOREGRESSIVE CONDITIONAL HETEROSKEDASTICITY (EGARCH) MODEL AND GJR GARCH ON INDIAN CRYPTOCURRENCIES'** In the partial fulfilment of the requirement for the award of the Degree of Bachelor of Technology in Mathematics And Computing and submitted to the Department of Applied Mathematics, Delhi Technological University, Delhi is an authentic record of our own, carried out during a period from August to November 2021, under the supervision of Dr. R. Srivastava.

The matter presented in this report has not been submitted by us for the award of any other degree of this or any other Institute/University. The work is in initial phase.

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CERTIFICATE

This is to certify that the Project titled '**VOLATILITY MODEL ANALYSIS USING EXPONENTIAL GENERALISED AUTOREGRESSIVE CONDITIONAL HETEROSKEDASTICITY (EGARCH) MODEL AND GJR GARCH ON INDIAN CRYPTOCURRENCIES**' which is submitted by Kunal Sharma (2K18/MC/060), & Rahul Sharma (2K18/MC/087) to Department of Applied Mathematics, Delhi Technological University is a record of the minor project work carried out by the students under my supervision. To the best of my knowledge this work has not been submitted in part or full for any degree or diploma to this university or elsewhere.

Place: Delhi

Date: 26/11/2021

Dr. R Srivastava

ABSTRACT

Recent development in the field of Digital Currencies such as Cryptocurrencies like Bitcoin, Ethereum, DogeCoin etc have piqued the attention and interest of Investors, Financial Researchers and Institutions, The concept of Cryptocurrencies' volatility is a burning issue at this time. The solid explosive type and extreme development rate of cryptocurrency increase more interest of investors; cause of more change prices the return rate bear cleverly carry out. This project besides determining the high rate volatility in cryptocurrency prices fits the Exponential Generalised Autoregressive Conditional Heteroskedasticity (EGARCH) and other similar models to the volatility of the digital currency. Model selection criteria will be carried out using Bayesian Information Criterion.

This study will support a direction for financiers to check the airiness of cryptocurrency and the effect of two together types of shocks (positive & negative) at the vacillation of cryptocurrency. A lot of studies of related to model the volatility of the Cryptocurrencies has been applied to predominantly upon the big three digital assets like Bitcoin, Ethereum and Ripple, here instead of that we will consider and model the Indian developed Cryptocurrencies namely Polygon MATIC and WazirX WRX.

ACKNOWLEDGEMENT

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We would like to take this opportunity to express our profound gratitude and deep regard to our project mentor **Dr. R. Srivastava**, for his exemplary guidance, valuable feedback and constant encouragement throughout the duration of the project. His valuable suggestions were of immense help throughout our project work. His perspective criticism kept us working to make this project in a much better way. Working under him was an extremely knowledgeable experience for us.

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KUNAL SHARMA

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INTRODUCTION

1.1 MOTIVATION AND PROBLEM STATEMENT

A cryptocurrency exists as a digital or virtual currency that is protected by cryptography, which makes it almost impossible to counterfeit or double-give. Many cryptocurrencies exist as decentralized networks established blockchain technology—a distributed ledger in force by a network of computers. A delineate feature of cryptocurrencies is that they are in most cases not circulated by any main expert, rendering bureaucracy in theory immune to management meddling or manipulation.

The increased interest in this form of digital assets has a pressing need for quantification of variation. As compared to the traditional currencies, these digital assets are highly volatile in nature and vary rapidly so much so that we cannot assume their exchange rate to be IID or Independently and Identically Distributed variables. The Generalized Autoregressive Conditional Heteroskedasticity model has been applied to real world currencies and have been found to be extremely useful for the study, while not much work has been done in their application for using the same models for digital currencies. Hence the motivation of the project lies in modelling the volatility of these currencies using GARCH and its variant model for understanding the nature of these digital assets.

The historical relevance of studying this problem lies in the fact that cryptocurrency suffer from extremely high volatility rates and hence the inability of the standard model to predict their upticks and downticks. BTC or Bitcoin is the most famous virtual currency out there which is highly involved in SMEs, other mostly used coins are Ethereum ETH and Ripple XRP. The biggest surge in the market capitalization of the cryptocurrency was observed back in the year 2017. From October 2016 to October 2017, Cryptocurrency market cap saw a surge of 8000x growth from approximately $ 10 million to $ 80 billion.

The Problem modelled here is the problem of prediction and forecasting volatility on exchange rate of cryptocurrencies, very little to no work has

been done on the Indian developed cryptocurrencies, that is why here instead of considering the biggest crypto by market cap, we consider the two biggest digital assets considered in India, namely MATIC coin developed by POLYGON and WRX developed by online brokerage WazirX.
The cryptocurrency returns are in essence uncorrelated with traditional asset classes such as bonds or shares of stock.
The two currencies under consideration are

Polygon MATIC

Ethereum token that helps the network of Polygon, which is a scaling solution for Ethereum. The objective of Polygon is to help provide more reliable and swift transactions on Ethereum using 2nd Layer Sidechains, which are a form of blockchain based technology that runs in parallel to the Ethereum main chain. The smart contract in Polygon can help users deposit Ethereum tokens and withdraw back to the Ethereum main chain.

WazirX WRX

This is a form of utility token of the company WazirX, based entirely upon the Binance Blockchain Technology And total supply of this right now is approximately 1 Billion.

1.2 OBJECTIVE

These cryptocurrency demonstrate some positive relation between volatility and shock in the Pre-crash period, but now since they are expanded their use and idolisation creates a pressing issue of measuring volatility. We try to find the best fitting GARCH model as described by BIC (Bayesian Inference Criterion). The objective of this project is to understand which conditional heteroskedasticity model can explain the diversified digital cryptocurrencies rate volatility.

1.3 SCOPE

The Volatility model analysis can help financiers understand the underlying stochastic behaviour of cryptocurrencies, it can help them to trade better and foresee an opportunity of buying or selling during the buy sell point problem. The model can be further improved by changing the parameters of the underlying GARCH and its variants to improve the fit and to give state of the art predictions. Smaller and asymmetric volatility response towards positive shocks in the price of the cryptocurrencies. Since the Indian cryptocurrency market is expected to grow more and more in the future, this comparative study can help deliver better investment returns by expanding the models to other cryptos.

CHAPTER 2

LITERATURE REVIEW

2.1 SCOPE

In the recent years, primarily after the Housing market crash of 2008, investors and financiers have started looking for the possibility of huge investment in cryptocurrencies (Dwyer 2015). These cryptocurrencies are generally used as forms of asset and not as exchange currencies in volatile markets resulting in a very varied and highly deviated digital climate (Katsiampa 2017). The first attempt to model these cryptocurrencies using statistical concepts like AR derived models started from one of the best papers (Balcilar 2017) and by (Dyhrberg 2017) which were some of the earliest attempts to use conditional heteroskedasticity for volatility forecasting and predictions. (Bouri 2016 and Cemak 2017) have studied the Power GARCH model to better fit the model in accordance with the Bayern Inference Criterion. Finally we took the most inspiration from the paper (Kyriazis and Daskalou 2019) which explains the need of volatility estimation during bearish and bullish cryptocurrency markets.

CHAPTER 3

METHODOLOGY

3.1 DATA DESCRIPTION

The data about cryptocurrencies under consideration (MATIC/INR and WRX/INR) has been downloaded from Investing.com website in a .csv format.

Polygon MATIC/INR

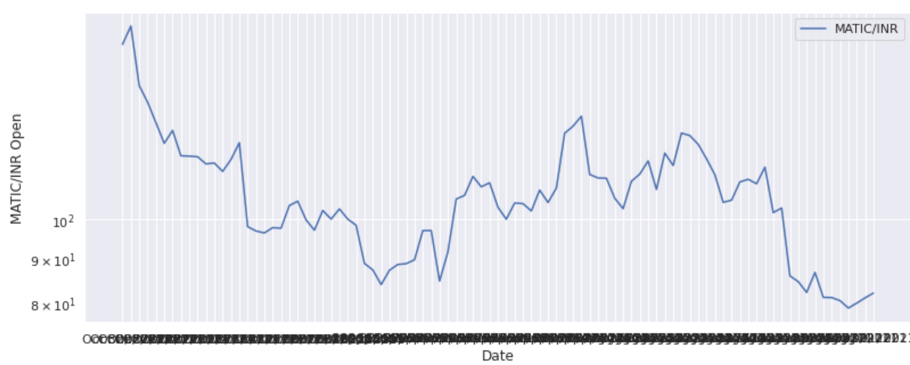

Fig 3.1: Historical Data of MATIC/INR

WazirX WRX/INR

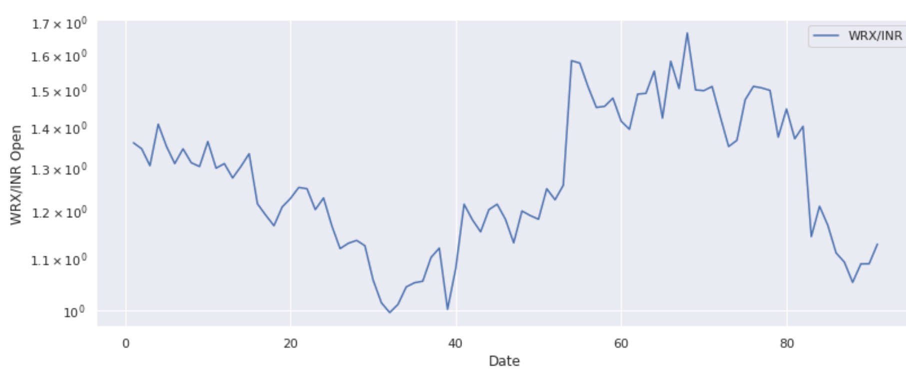

Fig 3.2: Historical Data of Wazir WRX/INR

3.2 FINANCIAL ENGINEERING AND GARCH MODELS

3.2.1 Autoregressive Model and their variants

AR models are a type of random processes that are used to describe time-varying processes in financial engineering. The component of autoregression specifies that output variable is linearly related to some of its previous values depending upon the parameters of the AR model

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t \qquad \text{.............. (3.1)}$$

where $\varphi_1, \ldots, \varphi_p$ are the "parameters" of the model, C is a constant, and ε_t is white noise.

$$X_t = c + \sum_{i=1}^{p} \varphi_i B^i X_t + \varepsilon_t \qquad \text{..................... (3.2)}$$

so that, moving the summation term to the left side and using polynomial

$$\phi[B]X_t = c + \varepsilon_t \,. \qquad \text{......................(3.3)}$$

The autoregressive model helps in predicting the values of a process at a certain future time based on the values of the processes that are known beforehand. The term means autoregressive means to bootstrap and generate and relate from itself. These AR processes are a form of stochastic processes having a degree of randomness.

Modification of this is the AR(p) model that is autoregressive with specific values of lag of y(t) which is used as predictor variables, the value of “p” in AR(p) model will be the order of the model, hence there are first order autoregressive process, second order and so on.

3.2.2 ARCH Model

In Financial engineering and Economics, the autoregressive conditional heteroskedasticity or ARCH is a type of statistical model for Time-Series Datasets that helps in understanding the variance of Error Term as a reason for the size of previous time periods and its error terms. These models are used in modelling of Time series data and volatility and clustering, which are time periods of ups and downs, ARCH belongs to a family of volatility models.

The error term is split into stochastic and time dependent standard deviation terms, helping formulate the size of the term.

$$\epsilon_t = \sigma_t z_t \qquad \text{.........................(3.4)}$$

Due to the random or stochastic variable, the series of time dependent variance will be modelled as

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \cdots + \alpha_q \epsilon_{t-q}^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 \qquad \text{..(3.5)}$$

Using the Lagrange Multiplier test, we can test the conditional heteroskedasticity of the residual error term.

3.2.3 GARCH Model

If the AR model is coupled with Moving Average generating ARMA and then we assume that for the error term, the model becomes Generalised ARCH, hence having two parameters namely p and q.

$$y_t = x_t' b + \epsilon_t \text{ and } \epsilon_t | \psi_{t-1} \sim \mathcal{N}(0, \sigma_t^2) \qquad \text{........... (3.6)}$$

$$\sigma_t^2 = \omega + \alpha_1 \epsilon_{t-1}^2 + \cdots + \alpha_q \epsilon_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + \cdots + \beta_p \sigma_{t-p}^2 = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 \qquad \text{........... (3.7)}$$

GARCH(p, q) model specification

P is the lag length of the Generalized ARCH model and q is the order of the model.

$$\rho = \frac{\sum_{t=i+1}^{T}(\hat{\epsilon}_t^2 - \hat{\sigma}_t^2)(\hat{\epsilon}_{t-1}^2 - \hat{\sigma}_{t-1}^2)}{\sum_{t=1}^{T}(\hat{\epsilon}_t^2 - \hat{\sigma}_t^2)^2}$$

……….(3.8)

Similarly there are multiple models that are available for modelling volatility, here besides GARCH we are going to use EGARCH and GJR GARCH.

EGARCH

This stands for Exponential Generalized ARCH model with (p, q) as

$$\log \sigma_t^2 = \omega + \sum_{k=1}^{q} \beta_k g(Z_{t-k}) + \sum_{k=1}^{p} \alpha_k \log \sigma_{t-k}^2$$

…………(3.9)

GJR GARCH

This stands for Glosten-Jagannathan-Runkle Generalized ARCH model with parameters (p, q) as

$$\sigma_t^2 = K + \delta\, \sigma_{t-1}^2 + \alpha\, \epsilon_{t-1}^2 + \phi\, \epsilon_{t-1}^2 I_{t-1}$$

where $I_{t-1} = 0$ if $\epsilon_{t-1} \geq 0$, and $I_{t-1} = 1$ if $\epsilon_{t-1} < 0$.

……(3.10)

CHAPTER 4

EXPERIMENTAL WORK

4.1 DATASET

We used one of the largest collections of Financial Data websites named as Investing.com to download and process the financial engineering data.
The dataset contains the information about MATIC/INR and WRX/INR indexed from their Date, having information regarding Price of 1 unit of the corresponding asset, for a given day the opening price, highest price achieved that data, lowest price achieved that day, the tidal volume of currency that are circulating in the market and %change or the one day return of the currency, a positive value means an uptick which suggests that one unit of that currency is now more expensive and vice versa for downticks.

MATIC/INR

The following images show the data and descriptive statistics about the Polygon MATIC/INR and WazirX WRX/INR Cryptocurrencies for short term period investments for 3 months.

Date	Price	Open	High	Low	Vol.	Change %
Oct 31, 2021	155.000	147.360	158.200	145.014	187.89K	5.18%
Oct 30, 2021	147.360	159.021	159.021	147.071	205.07K	-7.33%
Oct 29, 2021	159.021	166.969	174.427	142.000	424.20K	-4.76%
Oct 28, 2021	166.969	142.546	169.650	142.458	582.99K	17.13%
Oct 27, 2021	142.546	136.445	150.300	127.604	656.99K	4.47%
...	...	...	...	...	...	...
Aug 05, 2021	81.199	80.534	81.600	78.100	124.97K	0.83%
Aug 04, 2021	80.534	78.970	81.899	78.013	159.19K	1.98%
Aug 03, 2021	78.970	80.001	81.474	77.129	171.48K	-1.29%
Aug 02, 2021	80.001	81.117	82.872	78.610	81.05K	-1.38%
Aug 01, 2021	81.117	82.168	86.050	80.300	75.35K	-1.65%

[92 rows x 6 columns]
<class 'pandas.core.frame.DataFrame'>

TABLE 4.1 : Historical Data of MATIC/INR

```
           Date   Price   Open    High    Low     Vol.  Change %
0   Oct 31, 2021  1.4300  1.3820  1.5430  1.3710  21.10M   3.77%
1   Oct 30, 2021  1.3780  1.3590  1.3800  1.3070   8.08M   1.62%
2   Oct 29, 2021  1.3560  1.3440  1.3830  1.3350   6.81M   0.97%
3   Oct 28, 2021  1.3430  1.3030  1.3840  1.2590  14.06M   2.52%
4   Oct 27, 2021  1.3100  1.4060  1.4680  1.2670  15.22M  -6.76%
..           ...     ...     ...     ...     ...     ...     ...
87  Aug 05, 2021  1.1085  1.0916  1.1129  1.0526   5.82M   1.70%
88  Aug 04, 2021  1.0900  1.0518  1.1054  1.0320   4.40M   4.03%
89  Aug 03, 2021  1.0478  1.0881  1.0926  1.0373   4.09M  -3.60%
90  Aug 02, 2021  1.0869  1.0883  1.1266  1.0696   5.77M   0.13%
91  Aug 01, 2021  1.0855  1.1283  1.1600  1.0760   7.47M  -3.52%

[92 rows x 7 columns]
<class 'pandas.core.frame.DataFrame'>
<class 'pandas.core.frame.DataFrame'>
```

TABLE 4.2 : Historical Data of WRX/INR

```
print(maticDF.describe())
```

```
          Return        Low        High        Open       Price
count  91.000000  91.000000   91.000000   91.000000   91.000000
mean   -0.641882  99.252363  111.517615  106.164769  106.881165
std     6.143578  15.811043   18.039246   16.570331   16.926747
min   -22.297415  65.000000   81.474000   78.970000   78.970000
25%    -3.024194  86.250500   99.667000   96.999500   97.050000
50%    -0.146725  98.412000  110.784000  104.871000  105.159000
75%     2.921881 110.100000  119.899500  115.542000  115.917000
max    14.582280 147.071000  174.427000  166.969000  166.969000
```

```
[67] print(wrxDF.describe())
```

```
           Price       Open       High        Low     Return
count  91.000000  91.000000  91.000000  91.000000  91.000000
mean    1.282068   1.279454   1.339871   1.227203  -0.222879
std     0.163305   0.163272   0.171948   0.154054   5.513484
min     0.999000   0.995000   1.030000   0.962000 -20.245724
25%     1.160000   1.148950   1.210500   1.108000  -3.607066
50%     1.252000   1.252000   1.347000   1.200000  -0.279051
75%     1.410500   1.410000   1.491500   1.358850   2.409976
max     1.665400   1.662400   1.745400   1.490000  22.869692
```

TABLE 4.3 : Descriptive Statistics.

4.2 DATA PREPROCESSING

The data preprocessing stage involved cleaning of the data and extracting the relevant information from the /csv data file. Since all of the data contained is time-series data or time varying random/stochastic process, we need Hurst Exponent Function which is famous measure used in statistics for classifying the time series data and deriving the inferences of the level of difficulty in choosing apt model for series and carrying out predictions. Long term memory of time series is the key measure in deriving the hurst exponent of the equation. The rate at which these autocorrelations decrease as the lag increases.

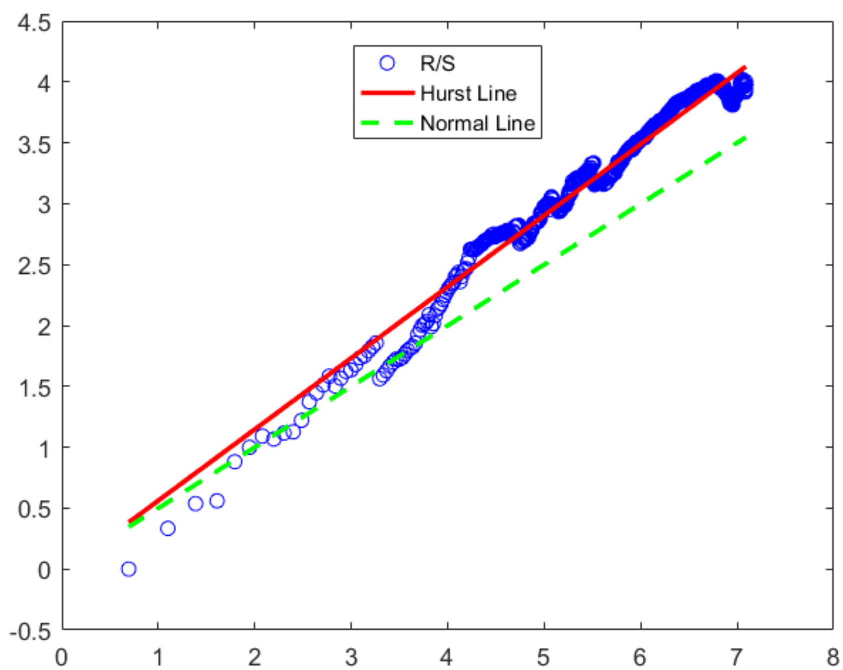

Fig 4.1: Hurst Point

Random Series - For Exponent in the vicinity of 0.5
Mean Reverting Series - For Exponent of value near 0
Trending - For Exponents near 1

4.2 EXPERIMENTAL CODING

After basic preprocessing of the data and passing the time series through Hurst Exponent, we then plot the Correlogram charts containing information regarding the Autocorrelation and Partial Autocorrelation, Probability plot and finally Q-stat and ADF for both of our crypto under consideration.

We then apply the GARCH, EGARCH and finally the GJR-GARCH model on both of our cryptocurrency data to find the short term investment plan by deriving relation between observed volatility of the stock and the volatility as observed from the model (GARCH, EGARCH, GJR GARCH).

Basic parameters of the Volatility model like Omega, Alpha, Gamma and Beta were found and the covariance estimate was robust in nature.

Finally basic descriptive statistics are obtained for understanding some of the general properties of cryptocurrency data like Quartiles, Mean, Std, interquartile ranges, skewness and kurtosis of MATIC/INR and WRX/INR.

CHAPTER 5

RESULTS

5.1 PERFORMANCE EVALUATION MEASURES

The following are the logs. Diff charts and Daily Volatility for MATIC/INR and WRX/INR Cryptocurrency which shows us the underlying Time - Series data, Probability plot, Autocorrelation and Partial Autocorrelation.

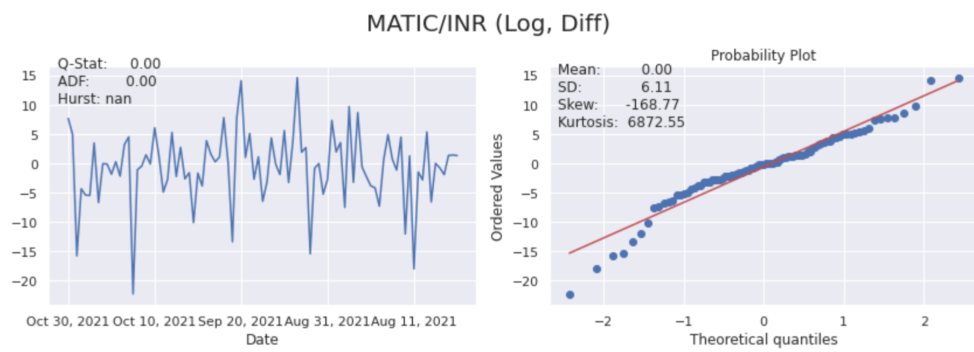

Fig 5.1: Log, Diff.MATIC/INR

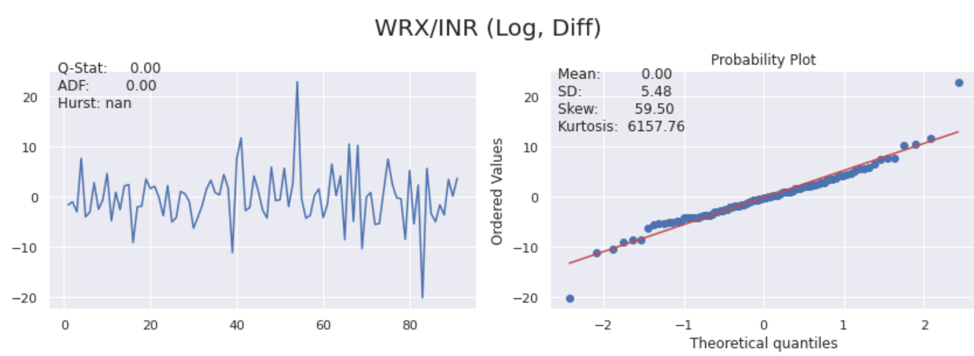

Fig 5.2: Log, Diff.WRX/INR

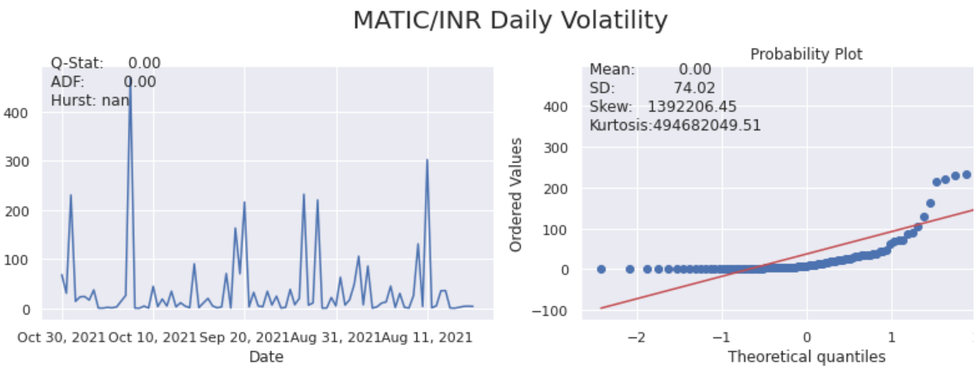

Fig 5.3: Daily Volatility Curve MATIC/INR

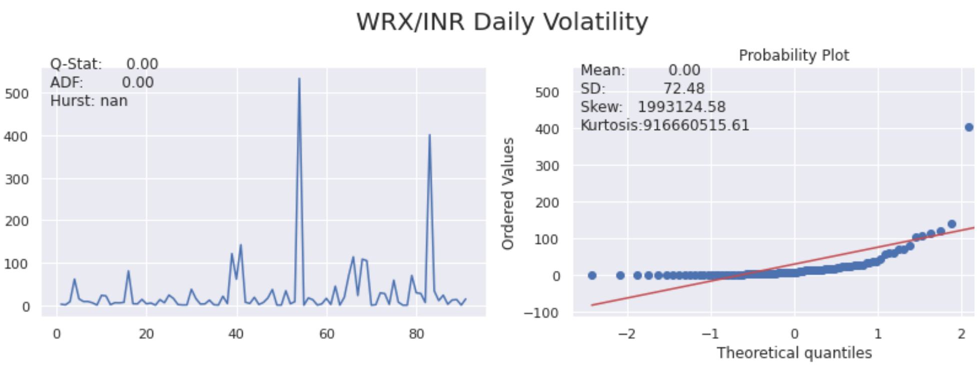

Fig 5.4: Daily Volatility Curve WRX/INR

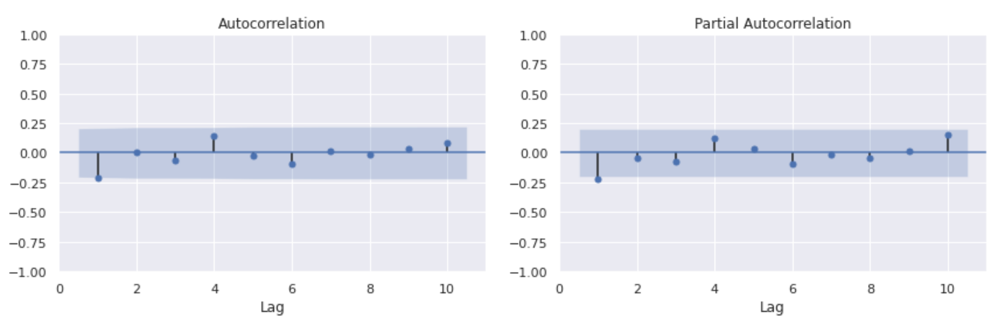

Fig 5.5: Autocorrelation

5.2 PREDICTED VS ACTUAL VOLATILITY OF THE DIGITAL ASSETS

```
                     Constant Mean - EGARCH Model Results
==========================================================================================
Dep. Variable:                      Return   R-squared:                           0.000
Mean Model:                  Constant Mean   Adj. R-squared:                      0.000
Vol Model:                          EGARCH   Log-Likelihood:                   -279.741
Distribution:      Standardized Student's t  AIC:                               571.482
Method:                 Maximum Likelihood   BIC:                               586.548
                                             No. Observations:                       91
Date:                     Thu, Nov 25 2021   Df Residuals:                           90
Time:                             10:52:12   Df Model:                                1
                                Mean Model
============================================================================
                 coef    std err          t      P>|t|      95.0% Conf. Int.
----------------------------------------------------------------------------
mu            -0.1638  3.602e-02     -4.547  5.436e-06 [ -0.234,-9.320e-02]
                              Volatility Model
===========================================================================
                 coef    std err          t      P>|t|     95.0% Conf. Int.
---------------------------------------------------------------------------
omega          0.2606  4.593e-06  5.674e+04      0.000   [  0.261,  0.261]
alpha[1]      -0.3848  2.534e-03   -151.841      0.000   [ -0.390, -0.380]
gamma[1]       0.0981  5.144e-03     19.066  4.804e-81 [8.800e-02,  0.108]
beta[1]        0.9258  8.264e-07  1.120e+06      0.000   [  0.926,  0.926]
                              Distribution
========================================================================
                 coef    std err          t      P>|t|  95.0% Conf. Int.
------------------------------------------------------------------------
nu             6.8365  5.469e-02    125.000      0.000 [  6.729,  6.944]
========================================================================

Covariance estimator: robust
```

TABLE 5.1 : Reports of EGARCH Model - For MATIC/INR

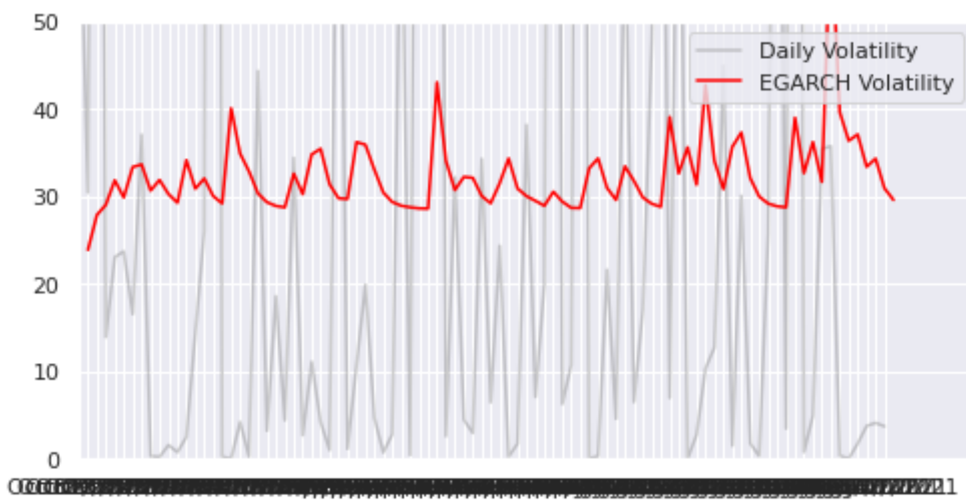

Fig 5.6 : Daily Vs EGARCH volatility

```
                     Constant Mean - GJR-GARCH Model Results
==============================================================================
Dep. Variable:                    Return   R-squared:                       0.000
Mean Model:                Constant Mean   Adj. R-squared:                  0.000
Vol Model:                     GJR-GARCH   Log-Likelihood:               -287.688
Distribution:      Standardized Student's t   AIC:                          587.376
Method:               Maximum Likelihood   BIC:                           602.442
                                           No. Observations:                   91
Date:                   Thu, Nov 25 2021   Df Residuals:                       90
Time:                           10:52:08   Df Model:                            1
                                 Mean Model
=========================================================================
                 coef    std err          t      P>|t|  95.0% Conf. Int.
-------------------------------------------------------------------------
mu            -0.1575      0.509     -0.310      0.757 [ -1.154,  0.839]
                              Volatility Model
=========================================================================
                 coef    std err          t      P>|t|  95.0% Conf. Int.
-------------------------------------------------------------------------
omega          3.3322      4.199      0.794      0.427 [ -4.898, 11.563]
alpha[1]       0.2118      0.589      0.359      0.719 [ -0.944,  1.367]
gamma[1]      -0.2118      0.622     -0.341      0.733 [ -1.431,  1.007]
beta[1]        0.8465      0.217      3.901  9.573e-05 [  0.421,  1.272]
                                 Distribution
=========================================================================
                 coef    std err          t      P>|t|  95.0% Conf. Int.
-------------------------------------------------------------------------
nu             3.4663      1.321      2.623  8.710e-03 [  0.876,  6.056]
=========================================================================

Covariance estimator: robust
```

TABLE 5.2: Reports of The GJR GARCH Model - For MATIC/INR

```
                       Constant Mean - EGARCH Model Results
==============================================================================
Dep. Variable:                    Return   R-squared:                       0.000
Mean Model:                Constant Mean   Adj. R-squared:                  0.000
Vol Model:                        EGARCH   Log-Likelihood:               -276.689
Distribution:      Standardized Student's t   AIC:                          565.378
Method:               Maximum Likelihood   BIC:                           580.443
                                           No. Observations:                   91
Date:                   Thu, Nov 25 2021   Df Residuals:                       90
Time:                           12:00:21   Df Model:                            1
                                 Mean Model
=========================================================================
                 coef    std err          t      P>|t|  95.0% Conf. Int.
-------------------------------------------------------------------------
mu            -0.4343      0.559     -0.776      0.437 [ -1.531,  0.662]
                              Volatility Model
=========================================================================
                 coef    std err          t      P>|t|  95.0% Conf. Int.
-------------------------------------------------------------------------
omega          1.9838      1.812      1.095      0.274 [ -1.568,  5.536]
alpha[1]       0.1000      0.249      0.401      0.689 [ -0.389,  0.589]
gamma[1]      -0.1022      0.487     -0.210      0.834 [ -1.056,  0.852]
beta[1]        0.4326      0.532      0.813      0.416 [ -0.611,  1.476]
                                 Distribution
=========================================================================
                 coef    std err          t      P>|t|  95.0% Conf. Int.
-------------------------------------------------------------------------
nu             3.6773      1.618      2.273  2.301e-02 [  0.507,  6.848]
=========================================================================

Covariance estimator: robust
```

TABLE 5.3: Reports of EGARCH Model - For WRX/INR

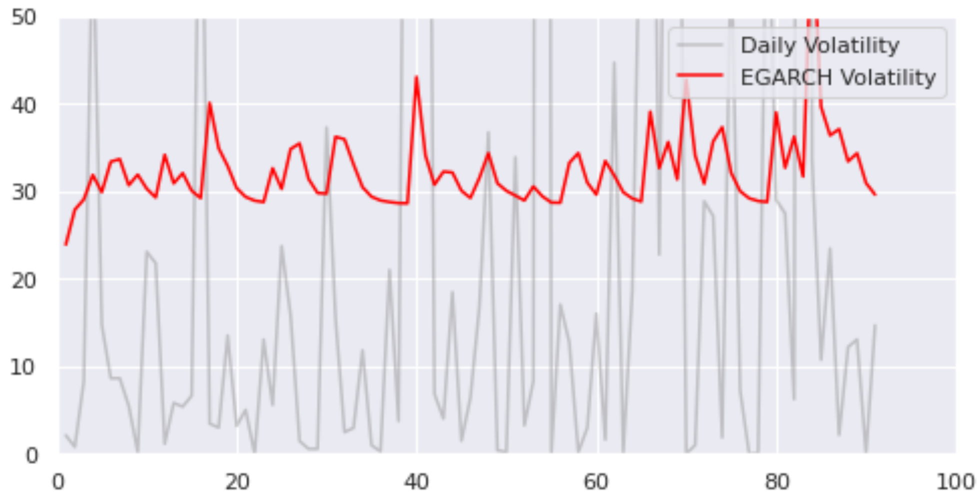

Fig 5.7 : Daily Vs EGARCH volatility

```
                     Constant Mean - GJR-GARCH Model Results
==================================================================================
Dep. Variable:                      Return   R-squared:                      0.000
Mean Model:                  Constant Mean   Adj. R-squared:                 0.000
Vol Model:                       GJR-GARCH   Log-Likelihood:              -275.154
Distribution:      Standardized Student's t   AIC:                          562.309
Method:                 Maximum Likelihood   BIC:                          577.374
                                             No. Observations:                  91
Date:                     Thu, Nov 25 2021   Df Residuals:                      90
Time:                             12:00:21   Df Model:                           1
                               Mean Model
========================================================================
                 coef    std err          t      P>|t|  95.0% Conf. Int.
------------------------------------------------------------------------
mu            -0.4445      0.545     -0.816      0.415 [ -1.512,  0.623]
                              Volatility Model
==============================================================================
                  coef    std err          t      P>|t|       95.0% Conf. Int.
------------------------------------------------------------------------------
omega           0.3464      1.090      0.318      0.751      [ -1.791,  2.484]
alpha[1]    6.8307e-14  4.436e-02  1.540e-12      1.000 [-8.695e-02,8.695e-02]
gamma[1]   -2.7903e-13  9.091e-02 -3.069e-12      1.000      [ -0.178,  0.178]
beta[1]         1.0000  5.977e-02     16.731  7.744e-63      [  0.883,  1.117]
                              Distribution
========================================================================
                 coef    std err          t      P>|t|  95.0% Conf. Int.
------------------------------------------------------------------------
nu             4.1056      1.538      2.669  7.598e-03 [  1.091,  7.120]
========================================================================

Covariance estimator: robust
```

TABLE 5.4: Reports of The GJR GARCH Model - For WRX/INR

5.3 ANALYSIS OF RESULTS

All the results shown above prove the application of Exponential GARCH and GJR GARCH on the Indian cryptocurrencies MATIC and WRX. The table summarises the parameters of the model for MATIC and EGARCH and the graph of expected volatility and actual volatility, similarly another table shows the relation between MATIC and GJR Garch. For the other dataset the table shows the relation between WRX and EGARCH and another table shows the relation between WRX and GJR GARCH.

We can analyse from the graphs that whenever the actual volatility of MATIC or WRX changes (upticks or downticks),a similar change can be observed in the graph of EGARCH and GJR GARCH, both the cryptos are slightly better mode-led using GARCH with higher BIC score. The underlying grey curve was the actual market and the red curve is the predicted, hence explaining the volatility of cryptos namely MATIC and WRX using Generalised Autoregressive Conditional Heteroskedasticity.

CHAPTER 6

CONCLUSION

In this project we proposed and compared two different Generalised Autoregressive Conditional Heteroskedasticity models for modelling volatility of value of Indian cryptocurrencies MATIC and WRX. The datasets for short term investment for 3 months was used and final results were displayed in terms of actual vs expected volatility, which shows positive correlation amongst them, hence proving that we can use Exponential Generalised Autoregressive Conditional Heteroskedasticity and GJR Generalised Autoregressive Conditional Heteroskedasticity for modelling the Indian cryptos. Autocorrelation and Partial Correlations were obtained along with daily volatility and volatility over 3 months. The final results suggest that the aim of the project has been fulfilled. For future scope of work and for Major Project - II, we are planning to take these variants of GARCH models and create forecasting models that can do predictive modelling and give predictions not only for upcoming days but a general trend of the values, finally we want to attain an optimum portfolio approach, in which we can find what cryptos to short and which to hold for getting maximum profits.

APPENDIX 1: CODE SNIPPETS

Most important algorithms

1. HURST EXPONENT FUNCTION

```
def hurst(ts):
    """Returns the Hurst Exponent of the time series vector ts"""
    # Create the range of lag values
    lags = range(2, 100)
    # Calculate the array of the variances of the lagged differences
    tau = [sqrt(std(subtract(ts[lag:], ts[:-lag]))) for lag in lags]
    # Use a linear fit to estimate the Hurst Exponent
    poly = polyfit(log(lags), log(tau), 1)
    # Return the Hurst exponent from the polyfit output
    return poly[0]*2.0
```

2. CORRELOGRAM PLOT

```
def plot_correlogram(x, lags=None, title=None):
    lags = min(10, int(len(x)/5)) if lags is None else lags
    fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(12, 8))
    x.plot(ax=axes[0][0])
    q_p = np.max(q_stat(acf(x, nlags=lags), len(x))[1])
    stats = f'Q-Stat: {np.max(q_p):>8.2f}\nADF: {adfuller(x)[1]:>11.2f} \nHurst:
     {round(hurst(x.values),2)}'
    axes[0][0].text(x=.02, y=.85, s=stats, transform=axes[0][0].transAxes)
    probplot(x, plot=axes[0][1])
    mean, var, skew, kurtosis = moment(x, moment=[1, 2, 3, 4])
    s = f'Mean: {mean:>12.2f}\nSD: {np.sqrt(var):>16.2f}\nSkew: {skew:12.2f}
    \nKurtosis:{kurtosis:9.2f}'
    axes[0][1].text(x=.02, y=.75, s=s, transform=axes[0][1].transAxes)
    plot_acf(x=x, lags=lags, zero=False, ax=axes[1][0])
    plot_pacf(x, lags=lags, zero=False, ax=axes[1][1])
    axes[1][0].set_xlabel('Lag')
    axes[1][1].set_xlabel('Lag')
    fig.suptitle(title, fontsize=20)
    fig.tight_layout()
    fig.subplots_adjust(top=.9)
```

3. RETURNS COLUMN GENERATION

```
maticDF['Return'] = np.log(maticDF['Open']).diff().mul(100)
maticDF = maticDF.dropna()
maticDF.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 91 entries, Oct 30, 2021 to Aug 01, 2021
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   Price     91 non-null     float64
 1   Open      91 non-null     float64
 2   High      91 non-null     float64
 3   Low       91 non-null     float64
 4   Vol.      91 non-null     object
 5   Change %  91 non-null     object
 6   Return    91 non-null     float64
dtypes: float64(5), object(2)
memory usage: 5.7+ KB
```

```
fig, ax1 = plt.subplots(figsize=(13, 5))
ax1.set_yscale('log')
ax1.plot(maticDF.index, maticDF.Open, color='b', label='MATIC/INR')
ax1.set_xlabel('Date')
ax1.set_ylabel('MATIC/INR Open')
ax1.legend()
plt.show()
```

4. PLOTTING CORRELOGRAM GRAPHS

```
plot_correlogram(maticDF['Return'], title='MATIC/INR (Log, Diff)')
```

```
plot_correlogram(wrxDF['Return'], title='WRX/INR (Log, Diff)')
```

```
plot_correlogram(maticDF['Return'].sub(maticDF['Return'].mean()).pow(2),
                 title='MATIC/INR Daily Volatility')
plot_correlogram(wrxDF['Return'].sub(wrxDF['Return'].mean()).pow(2),
                 title='WRX/INR Daily Volatility')
```

5. EGARCH AND GJR GARCH IMPLEMENTATION FOR MATIC AND WRX.

```
# Specify GJR-GARCH model assumptions
gjr_gm = arch_model(maticDF['Return'], p = 1, q = 1, o = 1, vol = 'GARCH',
                    dist = 't')
# Fit the model
gjrgm_result = gjr_gm.fit(disp = 'off')
# Print model fitting summary
print(gjrgm_result.summary())

# Specify EGARCH model assumptions
egarch_gm = arch_model(maticDF['Return'], p = 1, q = 1, o = 1, vol = 'EGARCH',
                       dist = 't')
# Fit the model
egarch_result = egarch_gm.fit(disp = 'off')
# Print model fitting summary
print(egarch_result.summary())
```

```
# Specify GJR-GARCH model assumptions
gjr_gm = arch_model(wrxDF['Return'], p = 1, q = 1, o = 1, vol = 'GARCH',
                    dist = 't')
# Fit the model
gjrgm_result = gjr_gm.fit(disp = 'off')
print(gjrgm_result.summary())
egarch_gm = arch_model(wrxDF['Return'], p = 1, q = 1, o = 1, vol = 'EGARCH',
                       dist = 't')
egarch_result = egarch_gm.fit(disp = 'off')
print(egarch_result.summary())
gjrgm_vol = gjrgm_result.conditional_volatility
egarch_vol = egarch_result.conditional_volatility
# Plot the actual returns
plt.axis([0, 100, 2, 8])
plt.plot(wrxDF['Return'], color = 'grey', alpha = 0.4, label = 'Price Returns')
plt.plot(egarch_vol, color = 'red', label = 'EGARCH Volatility')
plt.legend(loc = 'upper right')
plt.show()
# Print each models BIC
print(f'GJR-GARCH BIC: {gjrgm_result.bic}')
print(f'\nEGARCH BIC: {egarch_result.bic}')
```

6. EVALUATION AND PLOTTING

```
def evaluate(observation, forecast):
    # Call sklearn function to calculate MAE
    mae = mean_absolute_error(observation, forecast)
    print(f'Mean Absolute Error (MAE): {round(mae,3)}')
    # Call sklearn function to calculate MSE
    mse = mean_squared_error(observation, forecast)
    print(f'Mean Squared Error (MSE): {round(mse,3)}')
    return mae, mse

# Backtest model with MAE, MSE
evaluate(maticDF['Return'].sub(maticDF['Return'].mean()).pow(2), egarch_vol**2)
```

```
Mean Absolute Error (MAE): 41.381
Mean Squared Error (MSE): 5576.677
(41.380759771580514, 5576.67716087977)
```

```
# Plot the actual volatility
plt.axis([0,100,0,50])
plt.plot(maticDF['Return'].sub(maticDF['Return'].mean()).pow(2),
         color = 'grey', alpha = 0.4, label = 'Daily Volatility')

# Plot EGARCH  estimated volatility
plt.plot(egarch_vol**2, color = 'red', label = 'EGARCH Volatility')

plt.legend(loc = 'upper right')
plt.show()
```

All of the code used for modelling volatility has been hosted on Github here

REFERENCES

[1]. Gerald P. Dwyer, "The economics of Bitcoin and similar private digital currencies", Journal of Financial Stability, Volume 17, April 2017.

[2]. Paraskevi Katsiampa, "Volatility estimation for Bitcoin: A comparison of GARCH models", Economics Letters, Volume 158, September 2017.

[3]. Dyhrberg, Anne Haubo. 2016, " Bitcoin, gold and the dollar—A GARCH volatility analysis", Finance Research Letters 16: 85–92.

[4]. Balcilar, Mehmet, Elie Bouri, Rangan Gupta, and David Roubaud. 2017, "Can volume predict Bitcoin returns and volatility? A quantiles-based approach", Economic Modelling 64: 74–81.

[5]. Bouri, Elie, Georges Azzi, and Anne Haubo Dyhrberg. 2017, "On the return-volatility relationship in the Bitcoin Market around the price crash of 2013", Economics 11: 1–16.

[6]. Cermak, Vavrinec. 2017, "Can Bitcoin become a viable alternative to fiat currencies? An empirical analysis of Bitcoin's volatility based on a GARCH model", 30 September 2017, SSRN.

[7]. Nikolaos A. Kyriazis, "A survey on volatility fluctuations in the decentralized cryptocurrency financial assets", Journal of Risk and Financial management, Vol 14, 2021.

[8]. Christian Conrad, Anessa Custovic and Eric Ghysel, "Long- and Short-Term Cryptocurrency VolatilityComponents: A GARCH-MIDAS Analysis", Journal of Risk and Financial Management, 2018.