Role of Volatility in Realizing a Modern Payment System

Shubham Anand[1], Sarthak Gaurav[2], Meet Kathiriya[1], Vishwas T. Patil[1], Sudhanshu Raj[1], and R.K. Shyamasundar[1]

[1] Department of Computer Science and Engineering
[2] Shailesh J. Mehta School of Management
Indian Institute of Technology Bombay, Mumbai MH 400076, India

Abstract. Cryptocurrencies continue to attract the attention of global financial systems as an emerging payment system due to their efficient, transparent, and auditable mechanism to settle cross-border transactions. They come in two types depending on their underlying networks: permissionless (Bitcoin BTC) and quasi-permissioned (Ripple XRP). The permissionless type is unwelcome in the formal financial system due to obvious regulatory concerns. Whereas, the regulated, quasi-permissioned type has acceptability concerns due to the extreme volatility of the underlying currencies. The whole crypto market is typically characterized by high volatility due to factors that are not associated with traditional markets like equity, bond, commodities, crude et al. The concern about volatility discourages the acceptance of cryptocurrencies in traditional financial systems. Therefore, it is important to study the volatility of cryptocurrencies in order to know what causes sudden or frequent fluctuations in crypto markets. Though only a handful of cryptocurrencies like XRP are used by the formal financial system, the volatility in the crypto market reflects across all currencies. XRP exhibits comovement with BTC and other major cryptocurrencies in terms of volatility and price. Though BTC is not used by the formal financial system, but its volatility influences the cryptocurrencies used by them. This study will help financial institutions effectively mitigate the undue risk of incurring a high transaction cost while using cryptocurrency as a payment instrument. Our work sheds light on the relationship between transaction volume vis-a-vis the price of a cryptocurrency. We used ARIMA and SARIMA algorithms to forecast the transaction volume of BTC and XRP over a period of six months. Our trained model could successfully predict the transaction volatility for both BTC and XRP but not the volatility in their prices. The linear models we used fall short in price prediction; however, training the models over a longer period of time with additional inputs needs to be investigated. Since the size of a transaction block is fixed; only a limited number of high-fees transactions will be accommodated by block miners. Our result to predict volume volatility is useful in scheduling transactions in a block to negotiate transaction fees.

Keywords: cryptocurrency · volatility · causality.

1 Introduction

Over the past decade, the market for cryptocurrencies has grown remarkably [6]. There have not only been a proliferation of cryptocurrencies but also derivatives market of leading cryptocurrencies such as bitcoin (BTC) have developed. The transaction volume and market capitalization of cryptocurrencies has also increased remarkably, thereby positioning cryptocurrencies as a disruptive innovation in global financial markets. However, a representative feature of these digital assets is their high volatility [14]. Consequently, there are concerns [13] about stability of these digital assets relative to conventional assets. There is also regulatory uncertainty owing to ambiguity in classifying them as currencies, securities or money service [30].

Volatility of crypto assets is primarily driven by speculation by investors who bet on price movement and trade accordingly. Prospects of windfall from guessing the swings lures speculative traders as in securities and other financial markets. For instance, expecting price of a cryptocurrency to surge and buying before it does so or short selling before the price crashes are risks that traders and investors undertake routinely. However, there is evidence of comovement of prices among cryptocurrencies but lower correlation with conventional assets [4]. Another peculiarity of cryptocurrencies is that the technology changes are rapid and there is a lack of clarity among investors. The variety and volumes of transactions in cryptocurrency markets are driven by developments in blockchain, network designs and emerging architectures. Furthermore, with large population of noise traders, volatility in cryptocurrency markets as in the financial markets is inevitable. Traders or investors who make their decisions without advanced fundamental or technical analysis. As in the securities markets, cryptocurrency markets are also prone to noise trading and millions of amateur traders and investors are lured into taking positions with the prospects of considerable gains. Also, the barriers to entry are low.

Understanding the volatility of cryptocurrencies is necessary for the following three reasons: i) it provides insights into stability of the currencies; an important attribute for their greater adoption in formal transaction systems and suitability for enterprise smart-automation requirements. The speed of XRP transactions has implications on their volatility exposure relative to fiat currencies. For example, SWIFT transactions have much longer volatility exposures, whereas in XRP-based quasi real-time transactions, the need for hedging is obviated. Consequently, the associated cost is lower in crypto assets. This would enable crypto assets to be appealing for safe and secure payment systems such as Moneygram. ii) in contrast to permissionless flavor of cryptocurrency, the semi-permissioned flavor has a set of governing nodes/computers who may manipulate the liquidity in the network. iii) vis-a-vis centralized systems, decentralized systems offer high traceability and lower cost. But its volatility continues to be a barrier to adoption of decentralized payments systems and Stablecoins are emerging as an alternative [25]. Stablecoins have inbuilt price stabilization mechanisms to match the price of some other sovereign fiat currency that is stable [24].

In the context of volatility, it should be noted that there are fundamental differences between volatility of fiat currencies and cryptocurrencies. Fiat currencies are regulated and governed by central banks and their stability ensures liquidity in foreign exchange markets. There are well-established networks such as SWIFT that facilitate the movement of money across nations with the help of at least one stable currency. When multiple stable currencies are involved in the movement of money, each of the currencies in the basket affects the final amount represented in destination currency. Therefore, it is imperative to understand currency volatility and how volatility of cryptocurrencies compares with that of fiat currencies is critical for development of the market and decisions about regulation. The effect of factors on movements of a currency's exchange rate can be periodic (as time changes), asymmetric (affects only one side of the currency pair), associative (affects both sides of the currency pair). As volatility of cryptocurrencies continues to be debated, the stablecoin movement and need for stable crypto assets has gained attention for those seeking greater functionality and viability of the currencies. Attempts to peg cryptocurrencies to the US dollar (e.g., Tether) or assets such as oil (e.g., Petro cryptocurrency in Venezuela) to stabilize the value of the cryptocurrency promise to popularize use of these *stable* currencies for transactions. Cross-border payments also stand to benefit from payment solutions involving stable crypto assets. However, owing to lack of clarity on cryptocurrencies, there are concerns about their stability and even complete collapse of prices [12,7].

Key Findings:

- We found that our models predict the transaction volume of XRP and BTC with an accuracy that is significantly better than a baseline prediction model.
- *Accounting for seasonality in the time-series, SARIMA model adopted in the prediction of daily transaction volumes reduces prediction error as compared to the baseline model.*
- There is a negligible correlation between stock market volatility (VIX), XRP, and BTC's daily transaction volumes.
- Our findings suggest that cryptocurrency volatility is amenable to forecasting, using time-series models.
- *Transaction volumes and prices exhibit fundamentally different behaviour that needs deeper examination for assessment of stability of the cryptocurrencies.*

Organization: The following section provides background and motivation for this direction of work on the cryptocurrency volatility. Section 3 presents information about our datasets and approach for forcasting models. Section 4 and 5 present our results on forecast of BTC and XRP transaction volumes. Section 6 and 7 present our results on forecast of BTC and XRP prices. In Section 8, we present the related work along with comparative discussion. We conclude in Section 9 listing our findings highlighting this works potential future directions.

2 Background and Motivation

Traders and banks across the world are interested in understanding the volatility patterns in currencies and commodities in which they trade. It is imperative for them to understand currency volatility because it helps them to manage risks effectively; lack of it affects their profit margins adversely. There are empirical studies that highlight the patterns of volatility that are periodic [28]; for example, as stock markets open for trade in different major economies across the continents. Other factors such as news about macroeconomic/geo-political developments or regulatory announcements et al affect the exchange rates (thus the volatility) of the currencies [42,19].

There are numerous factors that are responsible for volatility of a currency. The more we understand about the factors the better we provision for our exposure to risks emanating from the volatility. As cryptocurrencies are emerging as an alternative investment instrument for a few, there is an interest to study the additional factors specefic to this class of assets' volatility. This study will not only be helpful for the investors and hedge fund managers but also the institutions that make use of this asset class to map conventional assets to crypto-assets in order to efficiently move conventional assets across the network (for example, remittance). While doing so, these institutions need to pay a transaction fees payable in the form of the native currency (i.e., cryptocurrency) of the respective network. Scheduling their asset movement transactions in order to minimize their transaction fees is a valid expectation, which can be assisted by a good understanding of the volatility patterns in respective network's cryptocurrency.

Though the phenomenon of volatility is well-studied for conventional asset classes, it is still evolving for cryptocurrencies. One of the distinguishing characteristics between the conventional class and the cryptocurrency class is that the former is well-regulated, mature, traded in specefic time slots whereas the cryptocurrency market is always open and largely unregulated. Technological and regulatory advancements are underway to inherit benefits of cryptocurrency networks into the conventional financial systems. XRP network is one such example where its operator Ripple tries to address the regulatory concerns by relying on tranditional banks as its entry and exit points for asset transfer (remittance) so that the valid criticism of AML, usually associated with Bitcoin like assets, is addressed effectively. Ripple allows its member banks to purchase XRPs so that these banks convert their conventional assets into XRP, transfer them to end-locations on XRP network, and then convert the transferred XRP into destination asset class. Though Ripple reduces the asset movement time and reduces the conventional currency's volatility affect on the value of asset being moved, there still remains the possibility of XRP being volatile due to three factors: i) inherent volatility of XRP caused by other cryptocurrencies connected to it at crypto-exchanges or via general sentiments of irrational actors in the network, ii) volatility in the conventional currency pegged with XRP at the transaction initiation point, iii) similarly, volatility in the conventional currency pegged with XRP at the transaction termination point. Therefore it is interesting to extend the study of causal relationship across conventional asset classes to cryto-class, considering the additional characteristics/constraints that are specefic to the nature of cryto-class and also the way they are designed and integrated to deliver a financial application. In Bitcoin network, the supply of BTC is deterministic and hard-coded in the network protocol – a strong constraint. Whereas, in XRP network, by design, all coins are pre-mined and a large volume is reserved as liquidity pool, but seldom used to control volatility as done by central banks in conventional finacial systems.

In this work we chose BTC and XRP because they represent two distict groups in this non-conventional asset class of cryptocurrencise. BTC network being permissionless and only governed by the hard-coded rules in its protocol with no provision for managed liquidity. XRP network being a semi-permissioned and by design takes into consideration the regulatory provisions of conventional financial system with the provision of liquidity by its operator (Ripple[3]). There is a evidence that BTC is the leader in cryptocurrencies and its volatility is closely followed by the other members in the class. Private investment bankers, hedge fund managers, retail customers from a unstable financial market rely on cryptocurrencies as an alternative to store of value. This affects supply side of the tokens (the unit of cryptocurrency) and causes volatility and dramatic price fluctuation. Until this asset class becomes large enough and as mature as conventional asset classes, volatility will remain its critical charesteristic and therefore study of cryptocurrency volatility is important.

3 Data and Approach

We run full-history servers for Bitcoin and XRP protocols. We extract the transaction data from the ledgers available on our servers. This allows us access all the transactions from the past that are executed on these two public blockchain networks. We use the time-series data from BTC and XRP ledgers to study volume and price volatility, their correlation, and potential forecasting methods. We use SARIMA (Seasonal Autoregressive Integrated Moving Average) model to forecast the transaction volume as well as price of the two cryptocurrencies.

The dataset consists of volume of daily transactions for BTC and XRP between the time period of July 2020 and July 2021. In January, 2018, XRP had reached an all-time-high of USD 3.84 and since then, it has experienced a fall. However, if there is comovement with BTC and altcoins, XRP is likely to rally, contributing to the volatility. Its ability to act as a hedge or a safe-haven is also influenced by the direction and strength of the comovements. The daily values of VIX Granger have been sourced from the CBOE (Chicago Board Options Exchange) website for the same time period of July 2020 and July 2021.

We follow forecasting models developed for various asset classes including currency and commodities, by contrast with conventional markets, crypto markets function continuously. This results in availability of high frequency data relative to conventional financial markets including stock markets that have specified

[3] https://ripple.com/insights/liquidity-explained/

opening and closing schedules in a day and remain shut over the weekend. Our approach to forecast the volume and price of BTC, XRP involves the following:

Step 1 - Stationarity Check: As a standard practice, we perform the Augmented Dickey-Fuller (ADF) test [32] and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test [36] to check for unit-root and trend-stationarity, respectively. The properties of a stationary time-series do not depend on the time at which the series is observed. The ADF tests the null hypotheses that a "unit-root" is present in the time-series. If a unit root is present, then the time series is non-stationary. Failure to reject the null implies non-stationarity whilst rejection of the null does not imply that the series is stationary.

Step 2 - SARIMA Parameter Identification: Following the tests of stationarity of the series, we identify the AR and MA parameters for SARIMA model. Given that the series is stationary, the order of integration (d) is zero. The orders of AR(p) and MA(q) are attained by plotting the auto correlation function (ACF) and partial autocorrelation function (PACF) plots of the series. The lag values from these plots give us the starting parameters.

Order p of the AR process is defined as the most extreme lag of the response variable that should be used as predictor in our model. We use the PACF to identify the lag order after which PACF plot "crosses" the upper confidence interval for the first time. These p lags will act as our features while forecasting the AR time series. Order q of the MA process is obtained from the ACF plot using the rule that it is the lag after which the ACF plot crosses the upper confidence interval for the first time.

To get statistical significance of empirically selected SARIMA parameters, information-criteria-based test such as AIC (Akaike Information Criterion) is widely used [22]. The aim of these tests is to find the parameters that give a model with the lowest value of the selected information criterion. AIC [31] is an estimator of out-of-sample prediction error and thereby relative quality of statistical models for a given set of data. Given a collection of models for the data, AIC estimates the quality of each model, relative to each of the other models. Suppose we have a statistical model of some data. Let k be the number of estimated parameters in the model. Let $\hat{L}$ be the maximum value of the likelihood function for the model. Then the AIC value of a model is:

$$AIC = 2k - 2ln(\hat{L}) \tag{1}$$

Step 3 - Granger Causality Test: The Granger causality test is a statistical hypothesis test for determining whether one time series is useful for forecasting another. If probability value is less than any α level, then the hypothesis would be rejected at that level.

In our time-series model specification, the dependent variable used for training and forecasting is logarithm of the volume of XRP. We follow SARIMA model in our analysis. In contrast to ARCH and GARCH models that model the second moment of the series or conditional variance, we are interested in modeling the first moment of the time-series, that is the conditional mean. ARIMA dynamic forecasting model has been attempted in limited number of studies to predict XRP prices [40]. Adjusting for seasonality in ARIMA forecasts for XRP and BTC transaction volumes is novel. The experiments are carried out using the following Python libraries: `statsmodels.tsa.stattools, statsmodels.api, pandas and pmdarima`. The `auto_arima` function is employed to arrive at the best fit ARIMA and SARIMA models for the considered time series. The train-test split has been undertaken in the ratio of 4:1 and the root mean squared error is utilised to assess the accuracy of test set predictions by the model. Further, the `grangercausalitytests` function is used to evaluate the causality levels between BTC's daily transaction volume and VIX Granger.

4 BTC Transaction Volume Forecast

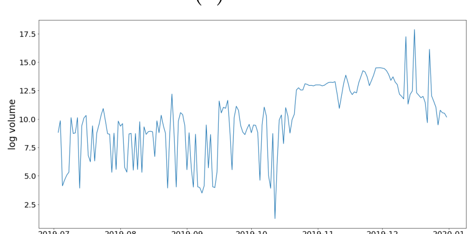
In this section, we present results of our analysis based on the steps leading to our prediction model for BTC's transaction volume.

4.1 Stationarity Check

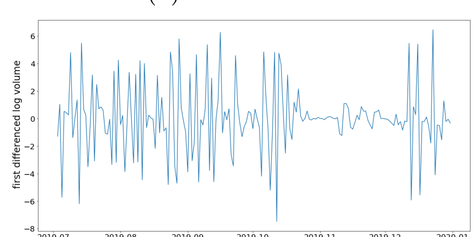
Figure 1a, shows raw data on transaction volume of BTC and Figure 1b shows the differentiated BTC trade volume vs time. Figure 3 (a) and (b) show the ACF and PACF plots respectively. In this test, we failed to reject the null, and therefore conclude that the BTC volume series (in logs) was trend-stationary (p-value 0.1). The KPSS test is used for testing the null hypothesis that a time series is stationary around a deterministic trend (i.e., trend-stationary) against the alternative of a unit-root. The null hypothesis in the KPSS test is that series is trend stationary. The alternative hypothesis is the presence of a unit-root.

Fig. 1: Trade volume vs time of Bitcoin

(a) Raw



(b) Differentiated



4.2 SARIMA Parameter Identification

Table 1 reports the AIC values for parameters in SARIMA model for BTC transaction volumes. The missing values (represented by a -) in these table are the instances where training of ARIMA model *did not converge*. Based on the significance of seasonality parameters that the `Auto-ARIMA` function in Python suggested, we trained our SARIMA (p,d,q) (P,D,Q) [2] model with parameters (5,0,3) (3,0,3) [7]. For this, we divided our transactions volume dataset into training and testing sets. The training and testing split has been carried out in the ratio of 4:1. We trained our SARIMA model on training set alone while keeping testing set hidden and then predicted transaction values for dates in testing set using our trained model. We also compared the testing data set with predicted data of BTC volumes in Figure 2 to see how our model performed.

Table 1: AIC values for various parameters (BTC Volume)

	ARIMA model	Intercept
1	(1,0,1)(0,0,0)[7]	17467.09
2	(0,0,0)(0,0,0)[7]	17771.62
3	(1,0,0)(1,0,0)[7]	17439.16
4	(0,0,1)(0,0,1)[7]	17516.55
5	(0,0,0)(0,0,0)[7]	18635.04
6	(1,0,0)(0,0,0)[7]	17465.56
7	(1,0,0)(2,0,0)[7]	17439.38
8	(1,0,0)(1,0,1)[7]	17440.38
9	(1,0,0)(0,0,1)[7]	17441.05
10	(1,0,0)(2,0,1)[7]	17438.08
11	(1,0,0)(3,0,1)[7]	17426.59
12	(1,0,0)(3,0,0)[7]	17435.57
13	(5,0,1)(3,0,3)[7]	inf, Tim
14	(5,0,3)(3,0,3)[7]	17373.96
15	(5,0,3)(2,0,3)[7]	17380.81
16	(5,0,3)(3,0,2)[7]	17380.24
17	(5,0,3)(4,0,3)[7]	17375.87
18	(5,0,3)(3,0,4)[7]	17376.93
19	(5,0,3)(2,0,2)[7]	17379.27
20	(5,0,3)(2,0,4)[7]	17381.82
21	(5,0,3)(4,0,2)[7]	inf, Tim
22	(5,0,3)(4,0,4)[7]	17379.99
23	(6,0,3)(3,0,3)[7]	17374.36
24	(5,0,4)(3,0,3)[7]	17378.44
25	(4,0,4)(3,0,3)[7]	17382.23
26	(6,0,2)(3,0,3)[7]	inf, Tim
27	(6,0,4)(3,0,3)[7]	17384.01
28	(5,0,3)(3,0,3)[7]	inf, Tim

In order to test our prediction, we compare our model against the baseline model which is simply the average of ground truth values. We use this value as the prediction for all days of the test set. Defining residual value as a variable named *res*.

$$res = predicted - truth \tag{2}$$

We define Root Sum Square Error (RSSE) as,

$$RSSE = \sqrt{\sum res^2} \tag{3}$$

Using the above formula for error calculation, with the baseline model, we get RSSE = 44881.84 Using the same formula on the SARIMA forecast model, we get RSSE = 40867.45. Clearly, the error is lower in the SARIMA forecast model as compared to the baseline model. This suggests that the SARIMA forecast model is better than the baseline average model for forecasting BTC transaction volume.

4.3 Granger Causality Test

We performed Granger Causality Test to assess the causality of BTC Daily Transaction Volume on VIX Granger and VIX Granger on BTC Daily Transaction Volume up to four lags. No significant causality exists: either of VIX Granger on BTC Daily Transaction Volume or of BTC Daily Transaction Volume on VIX Granger.

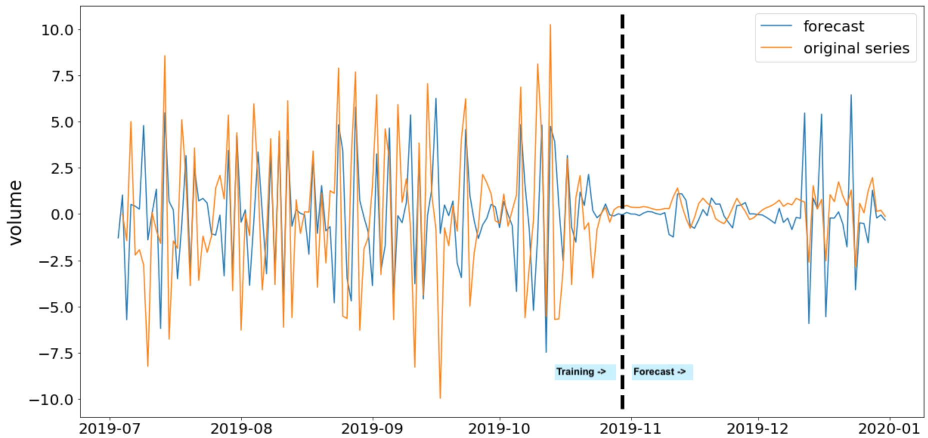


Fig. 2: Comparison of predicted values with actual series (for BTC volume)

Though studies such as [17] have shown that BTC daily transaction volume returns are significantly impacted by VIX Granger while analysing data of 2017 and 2018, the recent transaction volumes of BTC are found to hold insignificant levels of causal relationships with VIX Granger. Besides Granger Causality tests, the regular bidirectional causality between BTC transaction volumes and VIX Granger is also found to be much lower than the significance levels. This suggests that whilst Granger Causality between crypto currency may exist in a certain time period, it is not necessary to be so in another. This also necessitates the need for dynamically updating the forecast models for improved understanding of structural relationships.

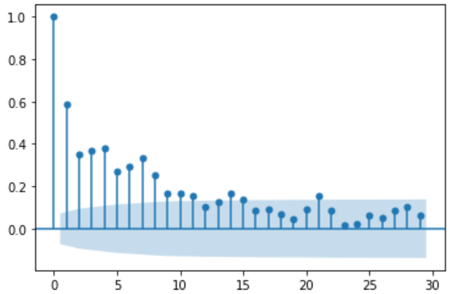
Results of Dickey-Fuller Test for BTC :	
Test Statistic	-9.695422e+00
p-value	1.107693e-16
#Lags Used	5.000000e+00
Number of Observations Used	1.760000e+02
Critical Value (5%)	-2.878106e+00
Critical Value (1%)	-3.468062e+00
Critical Value (10%)	-2.575602e+00
dtype: float64	

Results of KPSS Test for BTC :	
Test Statistic	0.066372
p-value	0.100000
Lags Used	14.000000
Critical Value (1%)	0.739000
Critical Value (10%)	0.347000
Critical Value (2.5%)	0.574000
Critical Value (5%)	0.463000
dtype: float64	

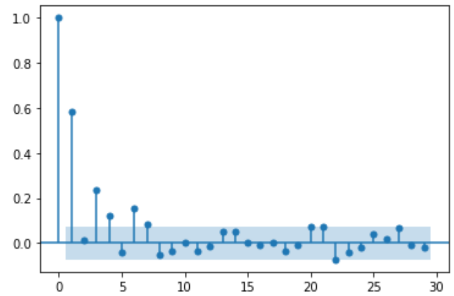
Results of Dickey-Fuller Test for XRP :	
Test Statistic	-1.336306e+01
p-value	5.379930e-25
#Lags Used	0.000000e+00
Number of Observations Used	1.830000e+02
Critical Value (5%)	-2.877467e+00
Critical Value (1%)	-3.466598e+00
Critical Value (10%)	-2.575260e+00
dtype: float64	

Results of KPSS Test for XRP :	
Test Statistic	0.122421
p-value	0.100000
Lags Used	14.000000
Critical Value (1%)	0.739000
Critical Value (10%)	0.347000
Critical Value (2.5%)	0.574000
Critical Value (5%)	0.463000
dtype: float64	

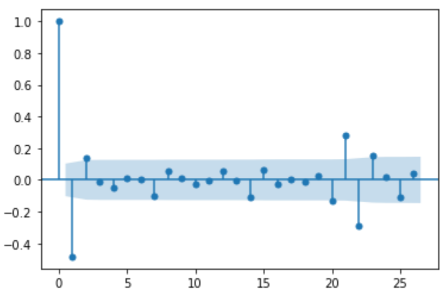
Table 2: ADF and KPSS test results for BTC and XRP currencies



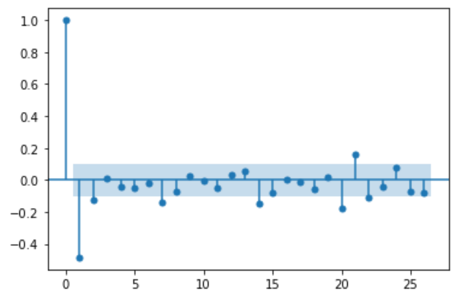
(a) ACF Plot for BTC



(b) PACF Plot for BTC



(c) ACF Plot for XRP



(d) PACF Plot for XRP

Fig. 3: ACF & PACF for first differencing of daily transaction volume

5 XRP Transaction Volume Forecast

5.1 Stationarity Check

Figure 4, shows raw data on transaction volume of XRP. The results of the ADF test for XRP transaction volumes suggests that non-stationarity can be rejected (p-value: 0.004). The KPSS test suggests that time-series for XRP volume is trend-stationary (p-value=0.1). Following the tests of stationarity of the series, we identified the parameters for SARIMA model. Figures 3 (c) and (d) report the ACF and PACF plots of the first differencing of XRP daily transaction volume. Analysis of the series using the Auto ARIMA function gives the best fit model is ARIMA for the series, which is ARIMA (2,1,2)(2,1,1)[7].

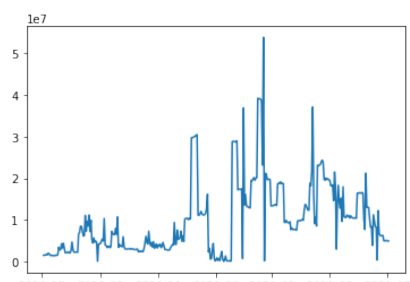


Fig. 4: XRP trade volume vs time

5.2 SARIMA Parameter Identification

Table 3 shows the AIC values for various parameter for XRP volume. We trained our SARIMA [2] model with parameters (2,1,2)(2,1,1)[7]. We also compared the testing data set with predicted data in Figure 2 to see how our model performed.

Figure 5b shows the testing set vs forecast data for XRP transaction volume. In order to test our prediction, we compare our model against baseline model which is simply the average of the ground truth values. We use this value as the prediction for all days of test set. Using the RSSE formula (as described in previous section) for error calculation, with baseline model, we get RSSE = 4227404.29. Using the same formula on the SARIMA forecast model, we get RSSE = 3972818.25. Clearly, the error is lower in the SARIMA forecast model as compared to the baseline model. This suggests that the SARIMA forecast model is better than the baseline average model.

	ARIMA model	Intercept
1	(1,1,1)(0,1,0)[7]	inf, Time
2	(0,1,0)(0,1,0)[7]	12765.019
3	(1,1,0)(1,1,0)[7]	12442.344
4	(0,1,1)(0,1,1)[7]	12267.730
5	(0,1,1)(0,1,0)[7]	inf, Time
6	(0,1,1)(1,1,1)[7]	12266.761
7	(0,1,1)(1,1,0)[7]	inf, Time
8	(0,1,1)(2,1,1)[7]	12259.751
9	(0,1,1)(2,1,0)[7]	inf, Time
10	(0,1,1)(3,1,1)[7]	12260.829
11	(0,1,1)(2,1,2)[7]	12261.102
12	(0,1,1)(1,1,2)[7]	12270.765
13	(0,1,1)(3,1,0)[7]	inf, Time
14	(2,1,2)(3,1,1)[7]	12164.200
15	(2,1,2)(2,1,2)[7]	12164.629
16	(2,1,2)(1,1,0)[7]	inf, Time
17	(2,1,2)(1,1,2)[7]	12171.276
18	(2,1,2)(3,1,0)[7]	inf, Time
19	(2,1,2)(3,1,2)[7]	12165.699
20	(1,1,2)(2,1,1)[7]	12164.273
21	(3,1,2)(2,1,1)[7]	12164.933
22	(2,1,3)(2,1,1)[7]	12186.092
23	(1,1,3)(2,1,1)[7]	12215.801
24	(3,1,3)(2,1,1)[7]	12163.642
25	(2,1,2)(2,1,1)[7]	12165.291

Table 3: AIC values for various parameters (XRP Volume)

5.3 Granger Causality Test

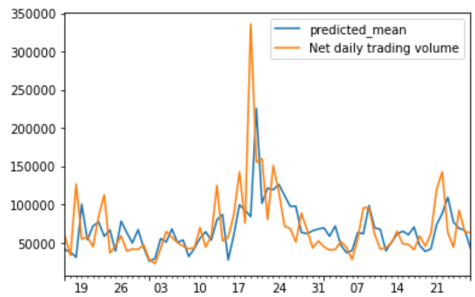
The Granger Causality Test has been performed to assess the causality of XRP Daily Transaction Volume on VIX Granger and VIX Granger on XRP Daily Transaction Volume up to four lags. No significant causality has been established either of VIX Granger on XRP Daily Transaction Volume or of XRP Daily Transaction Volume on VIX Granger. Besides Granger Causality Tests, the regular bidirectional correlation between XRP transaction volumes and VIX Granger is also found to be much lower than the significance levels.

6 Forecasting BTC Price

Figure 6a shows plot of raw data on closing price of BTC and Figure 6b shows the same data with first order differencing. We performed ADF and KPSS Test to check for stationarity. The results of the ADF test are for BTC closing price are depicted suggest that we cannot reject the null (p-value: 0.893420), indicating non-stationarity. To ensure stationarity, we first differenced the BTC price series.

Fig. 5: Comparison of testing set vs predicted values (between May & June 2021)

(a) for BTC



(b) for XRP

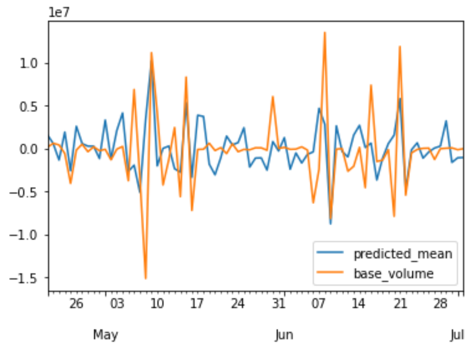
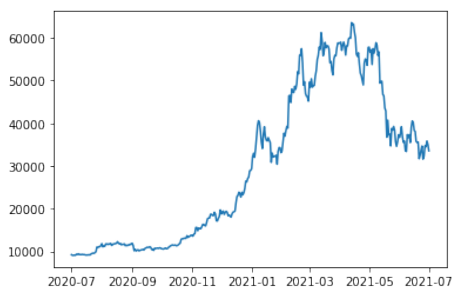
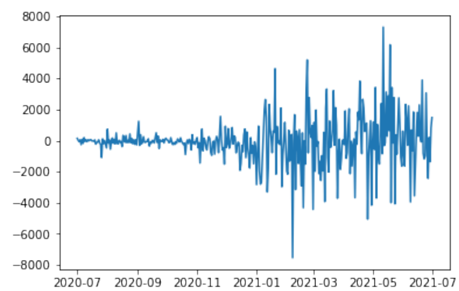


Fig. 6: Closing price of Bitcoin

(a) Raw



(b) First order differenciated



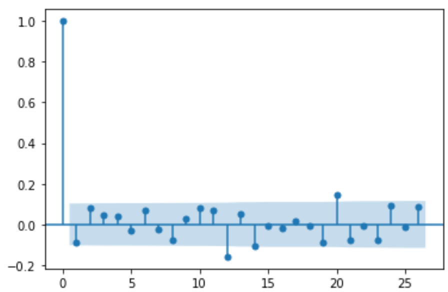
The results of the ADF test are for first order difference of BTC closing price results in rejection of the null of presence of unit-root (p 0.000)

In the KPSS test we found that the BTC price series was not trend-stationary (p=0.1). Therefore, to make it trend-stationary we performed first order differencing. We performed first order log differencing [15] i.e.,:

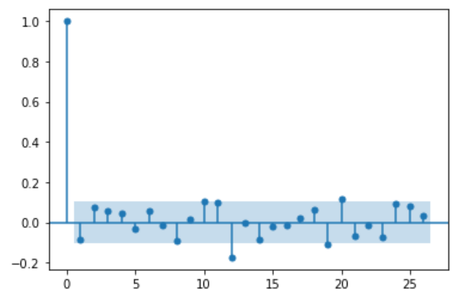
$$data(t) = data(t) - data(t-1) \tag{4}$$

Series is stationary. We reject the null that there is a unit root in the series, indicating that the time series is stationary. Following the tests of stationarity and differencing of the series, we identified the parameters for SARIMA (p,d,q) model. Figures 7 (a) and (b) report the ACF and PACF plots of the first differencing of BTC closing price. BTC Price could not be forecasted using SARIMA. The best fit model was ARIMA (0,0,0) (0,0,0) [0], indicating that none of the previous values bear notable significance in the predictions of BTC closing price.

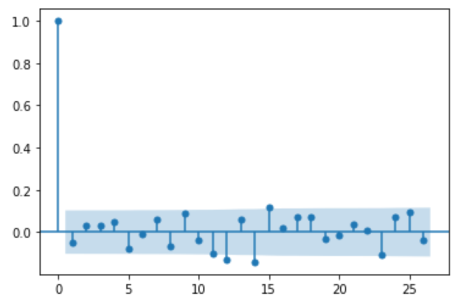
AIC results for BTC Price are reported in Table 4a.



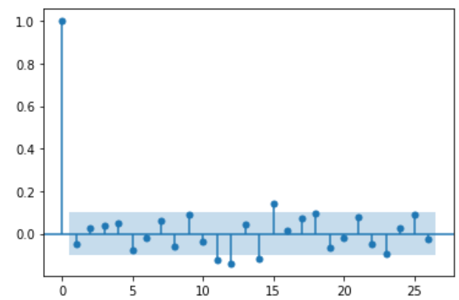
(a) ACF Plot for BTC



(b) PACF Plot for BTC



(c) ACF Plot for XRP



(d) PACF Plot for XRP

Fig. 7: ACF & PACF for first differencing of daily closing price

7 Forecasting XRP Price

In this section, we describe the data and methods, and present results of our analysis based on the steps leading to our prediction model.

Figure 8a shows raw data on closing price of XRP and Figure 8b shows the first order differencing on the same data. The results of the ADF test for XRP price suggests that we fail to reject the null of presence of a unit-root (p-value: 0.513). To remove the trend component of the time series and ensure stationarity, the first order differencing of the XRP closing price is performed.

The results of the ADF test are for First order difference of XRP closing price are depicted below (p-value: 0.000). Rejection of the null suggests that non-stationarity is not a concern for the first differenced series. The KPSS test suggests that the time-series for XRP price was trend-stationary (p=0.1). Figure 7 reports the ACF and PACF plots of the first differencing of XRP closing price.

Table 4b reports AIC values for XRP Price. As in the case of BTC Price, SARIMA is not able to forecast the XRP's price. The best fit model was ARIMA(0,0,0) (0,0,0) [0], indicating that none of the previous values bear notable significance in the predictions of XRP closing price.

Table 4: AIC values for various parameters

(a) BTC

	ARIMA model	Intercept
1	(2,0,2)(0,0,0)[0]	6395.608
2	(0,0,0)(0,0,0)[0]	6393.827
3	(1,0,0)(0,0,0)[0]	6392.967
4	(0,0,1)(0,0,0)[0]	6393.374
5	(0,0,0)(0,0,0)[0]	6392.516
6	(1,0,1)(0,0,0)[0]	6394.066

(b) XRP

	ARIMA model	Intercept
1	(2,0,2)(0,0,0)[0]	-925.765
2	(0,0,0)(0,0,0)[0]	-931.723
3	(1,0,0)(0,0,0)[0]	-930.675
4	(0,0,1)(0,0,0)[0]	-930.618
5	(0,0,0)(0,0,0)[0]	-933.569
6	(1,0,1)(0,0,0)[0]	-928.774

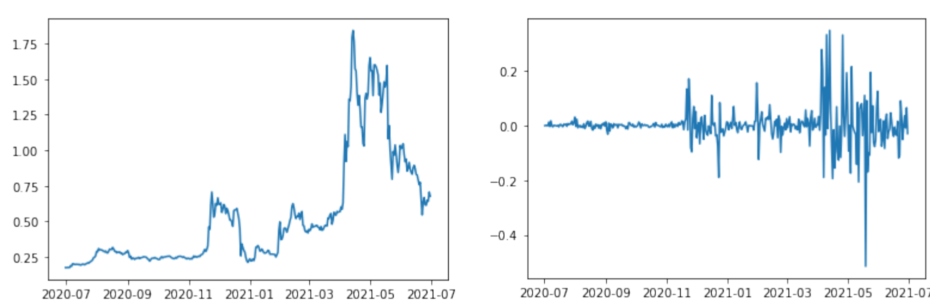
8 Related Work and Discussion

8.1 Forecasting Crypto-Volatility

The volatility forcasting models are not limited to the financial markets alone, they are also well-studied in other demand-oriented assets such as electricity, oil and gas. In [9], an investigation of the empirical properties of crude oil, natural gas, and electricity price volatility using a range of univariate and multivariate GARCH models is presented. Cryptocurrencies, unlike fiat currencies, are programmed to limit the supply of the currency as is the case with natural resources oil and gas. The scarcity in cryptocurrency can be considered as artificial scarcity, whereas that in the context of oil and gas is limited by the availability and exploration potential of the natural resources. Nevertheless, artificial scarcity does occur in the form of supply shocks that are often influenced by cartelisation of oil markets. In [28], the authors find that the intraday rates provide the most accurate forecasts for one-day and one-week forecast horizons, while implied volatilities are at least as accurate as the historical forecasts for one-month and three-month horizons. In [38,41], the authors present whether

Fig. 8: Closing price of XRP

(a) Raw (b) First order differenciated



evolution in the number of Google Internet searches for particular keywords can predict volatility in the market for a foreign currency. In a recent study [39], the authors use daily data for cryptocurrencies like Ripple, Ethereum, and Bitcoin, to test for the long memory property; they find that squared returns of these three cryptocurrencies have a significant long memory but best fitted GARCH model extensions differ. They find Hyperbolic GARCH (HYGARCH) model to be the best fitted model for Bitcoin whilst Fractional Integrated GARCH (FI-GARCH) model with skewed student distribution produces better estimations for Ethereum as well as Ripple returns. A recent study [10], using uncertainty as predictors of cryptocurrency volatility, finds that with respect to uncertainty variables the VIX-index is consistently negative correlated with occurence of bubble whilst the EPU-index largely exhibits positive associations with bubbles. Another study [20] surveys the evidence on return and volatility spillovers of cryptocurrencies and finds that BTC is the most influential in terms of transmitter as well as receiver of spillovers from cryptocurrencies and alternative assets. Ethereum, Litecoin, and Ripple XRP were found to be significantly interlinked with Bitcoin in the sense that there is a tendency to "follow the leader" in certain time windows. In [20], it is concluded that: although return spillovers are more pronounced, volatility spillovers often present a bi-directionality. Volatility shock transmission is detected among Bitcoin and sovereign fiat currencies, while economic policy uncertainty is not influential. There is also significant evidence on shock transmission among leading cryptocurrencies as well as spillover effects from cryptocurrency markets to conventional financial markets [16].

An attempt to forecast the price series of the crypto-market leader Bitcoin (BTC) using models such as ARIMA (Auto Regressive integrated Moving Average) have yielded inconclusive results [37]. A few studies have employed deep learning algorithms to predict cryptocurrency prices. Research has demonstrated notable improvements in BTC returns by enabling algorithms to effectively trade the currency based on the most confident predictions made [23]. Intricate Deep Learning (DL) models such as the Recurrent Neural Network (RNN), specifically the Long Short-Term Model (LSTM) have proved to be quite accurate in predicting the prices [8]. In [33], a comparison of BTC price forcasting using hybrid models such as LSTM and Deep Neural Network (DNN) is provided, and it is observed that the DNN models offered a far higher level of accuracy over other hybrid models. There have been a few studies that have noted that the improvement in accuracies of advanced DL models have not been as significant as expected.

A few studies have emphasized on the fractal and multifractal analyses of cryptocurrency price data. In [11], Bariveria demonstrates through the Rescaled Hurst Exponent method and the Detrended Fluctuation Analysis (DFA) method that the volatility of BTC daily prices have a pronounced degree of long memory, an indication of the volatility clustering inherent in cryptocurrencies. Besides, predominance in short amplitude volatility and anti-persistency in the Hurst Exponent value and the magnitude of multifractal aspect of the time series denote an absence of characteristic stability in BTC prices and the rampant price fluctuations are believed to be a result of insufficient regulation of the cryptocurrency [34]. Taking structural breaks into cognizance, the prices of 12 major cryptocurrencies have been found to display volatility-persistence, which needs to be given due consideration by investors in their long-term forecasting practices of cryptocurrency prices [1].

8.2 Causation in Crypto-Volatility

Studies on interconnections between volatility and shocks among large cryptocurrencies reveal that Litecoin and BTC lie at the heart of the volatility interconnections. Ripple has a noticeable tendency to absorb negative-return jolts in the prices of other cryptocurrencies while Dash and Ethereum exhibit very insignificant interconnectedness with the volatilities of other major cryptocurrencies in the economy [29]. As to the relationship between the S&P 500 and volatility in cryptocurrency prices, the GARCH-MIDAS models have been employed and results show that volatility realized in the S&P 500 is very likely to bear a significant but negative impact on the cryptocurrency prices in terms of their long-term volatility. Also, there has been a substantial positive correlation established between the BTC price volatility and the fluctuations in the Baltic Dry Index [5]. On the other hand, the impact of oil markets on the macroeconomic attributes of various regimes have been found to influence the degrees of volatility in major cryptocurrencies. Investors in such case are found to transition in favour of cryptocurrency markets as a measure to hedge against sovereign uncertainties arising out of oil shocks [21]. Focusing on the relative convergences among the prices of eight predominant cryptocurrencies, the market microstructure is found to be the most significant driver of the convergences and the confluences are significantly noted among cryptocurrencies with diverse functionalities. Moreover, studies have also encountered close relationships between the introduction of BTC futures contract in the Chicago Board of Exchange and the convergence in prices of major cryptocurrencies – owing to the widespread emergence of cryptocurrency backed instruments, in kind as well as scale, in the open economy [26]. Focusing on the effect of "nature of a blockchain" on the price volatility of cryptocurrency, in [35], Saleh points out that price-volatility is a dominant feature of cryptocurrencies with Proof of Work (PoW) blockchain, since such blockchain tend to execute passive monetary policies, which are predominantly reactive in nature. As an alternative consensus algorithm – Proof of Burn (POB) adopts a proactive approach towards monetary policy, reducing any whimsical volatility in the system. POB can only reduce the liquidity and it is irreversible, whereas in XRP setup the liquidity can be increased on demand and therefore we believe it is a good/practical candidate for our investigation of volatility.

8.3 Supporting Observations

- Correlation tests: The bidirectional correlation between BTC daily transaction volumes and VIX Granger for the period of July 2020 to July 2021 has been computed and is found to be 0.3655.

- Engle Test: Using Engle Test for ARCH, we fail to reject the null hypotheses and failure to reject the null hypothesis implies our time-series data is not homoscedastic.
- Granger Causality Test for BTC & XRP Volumes: The Granger Causality Test has been performed to assess the causality of BTC & XRP Daily Transaction Volume on VIX Granger and VIX Granger on BTC & XRP Daily Transaction Volume up to four lags. Both of these tests show no significant causality. The parameters used to test causality of XRP daily volume on VIX Ganger are provided in Table 9.

9 Conclusions

We find that SARIMA (seasonality adjusted ARIMA) models satisfactorily predict the transaction volume of both XRP and BTC, but not the price. Accounting for seasonality in the time-series, prediction of daily transaction volumes posits a much lower prediction error as compared to the baseline model. Furthermore, Granger causality tests between a popular index of stock market volatility and BTC/XRP daily transaction volumes reveal a negligible correlation. We posit that a deeper understanding of volatility of cryptocurrencies, particularly those associated with semi-permissioned blockchain such as XRP will shed a light on their suitability for financial transactions including cross-border transfers and CBDCs. We intend to make use of AI/ML techniques to further investigate this research direction; further improving our current findings using SARIMA.

Our study contributes to the growing literature on volatility of cryptocurrencies (e.g., [18]). We aim to continue this research to find alternative model specifications on the lines of [39] that use alternative time-series model specifications. Our current work is specifically useful in predicting the transactions volume (volatility) of prominent global fiat currencies on XRP network. This capability can be used in Ripple's XRP network for: i) correcting transaction ordering flaws leading to temporary volatility in the network, ii) identifying source of volatility by checking whether the volatility in XRP is following the volatility in other stable currencies, iii) preventing exploitation of the Ripple's network; i.e., a few trusted users from UNL taking advantage of predicting the volume and blocking or slowing down the network. From a market development perspective, there are concerns that higher volatility, trading volume may indicate the presence of bubbles across cryptocurrencies. We would also like to find out correlations, if any, between a specific class of events (including the ones listed in [3]) and the volatility on XRP network – and its impact on transaction fees – this will help financial entities to provision their transactions better. Transaction volumes and prices exhibit fundamentally different behaviour that needs deeper examination for assessment of stability of the cryptocurrencies.

References

1. Aikins, A.E.J., Alberiko, G.A.L., Godfrey, M., Fatima, R.R.: Volatility persistence in cryptocurrency markets under structural breaks. International Review of Eco-

nomics & Finance **69**, 680–691 (2020)
2. Ariyo, A.A., Adewumi, A.O., Ayo, C.K.: Stock price prediction using the ARIMA model. In: 2014 UKSim-AMSS 16th International Conference on Computer Modelling and Simulation. pp. 106–112. IEEE (2014)
3. Best, R., Littman, K., Krishnamurthy, P., Tenreiro, J.G., Bliss, D., Enright, J.O., Waxman, D.A., Daniels, J.A.: SEC's Complaint agains Ripple's Distribution of XRP. https://www.sec.gov/litigation/complaints/2020/comp-pr2020-338.pdf (2020), [Online; accessed 10-11-2021]
4. Borri, N.: Conditional tail-risk in cryptocurrency markets. Journal of Empirical Finance **50**, 1–19 (2019)
5. C., C., A., C., E., G.: Long-and short-term cryptocurrency volatility components: A GARCH-MIDAS analysis. Journal of Risk and Financial Management **11** (2020)
6. Catalini, C., Gans, J.S.: Some simple economics of the blockchain. Communications of the ACM **63**(7), 8090 (Jun 2020)
7. Cheah, E.T., Fry, J.: Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin. Economics Letters **130**, 32–36 (2015)
8. D., O.J., E., H.M.: Forecasting bitcoin pricing with hybrid models: A review of the literature. Int. J. of Advanced Engineering Research and Science **6**, 161–164 (2019)
9. Efimova, O., Serletis, A.: Energy markets volatility modelling using GARCH. Energy Economics **43**, 264 – 273 (2014)
10. Enoksen, F., Landsnes, C., Luivjansk, K., Molnr", P.: Understanding risk of bubbles in cryptocurrencies. Journal of Economic Behavior & Organization **176**, 129–144 (2020)
11. F., B.A.: The inefficiency of Bitcoin revisited: A dynamic approach. Economics Letters **161**, 1–4 (2017)
12. Fry, J., Cheah, E.T.: Negative bubbles and shocks in cryptocurrency markets. International Review of Financial Analysis **47**, 343–352 (2016)
13. G7 Working Group on Stablecoins: Investigating the impact of global stablecoins. https://www.bis.org/cpmi/publ/d187.pdf (2019), [Online; access 20-08-2022]
14. Garca-Monlen,F. and Danvila-del-Valle,I. and Lara,F. J.: Intrinsic value in crypto currencies. Technological Forecasting and Social Change **162** (2021)
15. J, J.G.: Determining the degree of differencing for time series via the log spectrum. Journal of Time Series Analysis **3**(3), 177–183 (1982)
16. J., L., A, S.: Volatility in the Cryptocurrency Market. Open Economies Review **30**, 779–811 (2019)
17. K, M.R., L, D.P.: Time series analysis of Cryptocurrency returns and volatilities. Journal of Economics and Finance **45**(1), 75–94 (2021)
18. Katsiampa, P.: Volatility estimation for Bitcoin: A comparison of GARCH models. Economics Letters **158**, 3–6 (2017)
19. Kim, Y.B., Kim, J., Kim, W., Im, J., Kim, T., Kang, S., Kim, C.H.: Predicting fluctuations in cryptocurrency transactions based on user comments and replies. PLOS ONE **11**, e0161197 (08 2016)
20. Kyriazis, N.A., Daskalou, K., Arampatzis, M., Prassa, P., Papaioannou, E.: Estimating the volatility of cryptocurrencies during bearish markets by employing GARCH models. Helyon **5**(8), e02239 (2019)
21. L., Y., J., N., L., H.: Understanding cryptocurrency volatility: The role of oil market shocks. International Review of Economics & Finance **72**, 233–253 (2021)
22. Liew, V.K.S.: On autoregressive order selection criteria. Computational Economics 0404001, University Library of Munich, Germany. (2004)

23. M., A., D., S.: Trading Bitcoin and online time series prediction. NIPS 2016 Time Series Workshop pp. 1–15 (2017)
24. M., M., K., I., S., O., H., T.: What is stablecoin?: A survey on price stabilization mechanisms for decentralized payment systems. In: Proceedings of 8th International Congress on Advanced Applied Informatics, IIAI-AAI. pp. 60–66 (2019)
25. Members, L.A.: The Libra Blockchain. https://wp.diem.com/en-US/wp-content/uploads/sites/23/2020/04/Libra_WhitePaperV2_April2020.pdf (2020), Online; accessed 20-08-2022
26. N., A., D., K., E., P.J.: Convergence in cryptocurrency prices? the role of market microstructure. Finance Research Letters **40** (2021)
27. Patrick, B.: Robustness of the Ljung-Box test and its rank equivalent. Available at SSRN 443560 (2002)
28. Pong, S., Shackleton, M.B., Taylor, S.J., Xu, X.: Forecasting currency volatility: A comparison of implied volatilities and AR(FI)MA models. Journal of Banking & Finance **28**(10), 2541 – 2563 (2004)
29. Q., J., E., B., M., L.C.K., D., R.: Dynamic connectedness and integration in cryptocurrency markets. International Review of Financial Analysis **63**, 257–272 (2019)
30. R., W., Y., M., N., I., S., W.: Is Bitcoin a currency, a technology-based product, or something else? Technological Forecasting and Social Change **151** (2020)
31. Ritei, S.: Selection of the order of an autoregressive model by Akaike's information criterion. Biometrika **63**(1), 117–126 (1976)
32. Rizwan, M.: Augmented Dickey Fuller test. SSRN (2011)
33. S., J., J., K., H., I.: A Comparative Study of Bitcoin Price Prediction Using Deep Learning. Mathematics **7** (2019)
34. S., S., V., B., S., B., S., L., S., U.G.: The high frequency multifractal properties of Bitcoin. Physica A: Statistical Mechanics and Its Applications **520**, 62–71 (2019)
35. Saleh, F.: Volatility and welfare in a crypto economy. SSRN 3235467 (2019)
36. Shin, Y., Schmidt, P.: The KPSS stationarity test as a unit root test. Economics Letters **38**(4), 387–392 (1992)
37. Siami-Namini, S., N., T., S., N.A.: A Comparison of ARIMA and LSTM in Forecasting Time Series. 17th IEEE International Conference on Machine Learning and Applications (ICMLA) (2018)
38. Smith, G.P.: Google Internet search activity and volatility prediction in the market for foreign currency. Finance Research Letters **9**(2), 103 – 110 (2012)
39. Soylu P.K. and Okur M. and atkka . and Altintig Z.A.: Long memory in the volatility of selected cryptocurrencies: Bitcoin, Ethereum and Ripple. Journal of Risk and Financial Management **136** (2020)
40. Sudipta Majumdar, F.A.: Innovation and Intellectual Property Rights. In: Machine Learning and Artificial Intelligence in Financial Services. IGI Global (2019)
41. Vlastakis, N., Markellos, R.N.: Information demand and stock market volatility. Journal of Banking & Finance **36**(6), 1808 – 1821 (2012)
42. Zhang, W., Wang, P., Li, X., Shen, D.: Some stylized facts of the cryptocurrency market. Applied Economics **50**(55), 5950–5965 (2018)

A Prediction of Transaction Volumes

A.1 AIC, BIC, and HQIC tests to confirm parameters

To get a statistical significance of empirically selected ARIMA parameters, AIC, BIC and HQIC tests are widely used in the literature [22]. The aim of these tests is to find the parameters that gives a model with the lowest value of the selected information criterion.

q → / p ↓	0	1	2
0	709.553588	594.475659	559.54405
1	653.548756	-	-
2	632.871719	-	-
3	615.542656	567.333071	-
4	603.816827	566.505444	-
5	602.270328	567.420411	-

Table 5: AIC values for various parameters (for BTC)

q → / p ↓	0	1	2
0	715.111835	602.813030	570.660544
1	661.886127	-	-
2	643.988213	-	-
3	629.438273	584.007812	-
4	620.491568	585.959309	-
5	621.724192	589.653399	-

Table 6: BIC values for various parameters (for BTC)

In above Tables 5, 6, and 7, the missing values (represented by -) are the instances where training of ARIMA model *did not converge*.

It can be inferred that ARIMA model is giving lower value of selected information criterion for q value of 1 than for q value of 0 and for q value of 1, BIC and HQIC are lowest for p value of 3 while AIC is lowest for p value of 2 although not by a large margin. These observations verify that the empirically estimated p and q values are statistically sound and can be used for forecasting of our timeseries.

A.2 Ljung-Box Test Hypotheses

A significant p-value in this test rejects the null hypothesis that the time series isn't autocorrelated. We performed this test [27] on the residuals of our timeseries.

q → / p ↓	0	1	2
0	711.810617	597.861202	564.058107
1	656.934299	-	-
2	637.385776	-	-
3	621.185227	574.104157	-
4	610.587913	574.405044	-
5	610.169928	576.448525	-

Table 7: HQIC values for various pameters (for BTC)

lag	lb_pvalue	lb_stat
1	0.593384	0.285091
2	0.768140	0.527566
3	0.729821	1.297103
4	0.278596	5.085906
5	0.391157	5.206886
6	0.485033	5.470467
7	0.328934	8.041664
8	0.208098	10.888496
9	0.091503	14.979415
10	0.132357	14.991899

Table 8: Ljung-box test results at different lags

A.3 ARIMA prediction and results for XRP transactions volume

We trained our ARIMA [2] model with parameters (3,1,1)[4]. For this we divided our transactions volume data set of 1st July 2019 to 31st December 2019 into training and testing set. The training set consists of transactions from 1st July 2019 to 31st October 2019 and testing set consists of transactions from 1st November 2019 to 31st December 2019. We trained our ARIMA model on training set alone while keeping testing set hidden and then predicted transaction values for dates in testing set using trained model. We get RSSE = 14.28 with baseline model and we get RSSE = 11.75 with ARIMA forecast model. Clearly, the error is lower in the ARIMA forecast model as compared to the baseline model. This suggests that the ARIMA forecast model is better than the baseline average model.

To see if the residual in our ARIMA model is not skewed, we plot the residual and compare it with Gaussian distribution in Figure 9. The mean and standard deviation come out to be 0.08 and 2.52 respectively. We also plot the gaussian distribution with dotted line with the same mean and standard deviation for comparison. We observe that the mean is around 0 and the distribution is similar

[4] using implementation from `statsmodels` library of Python

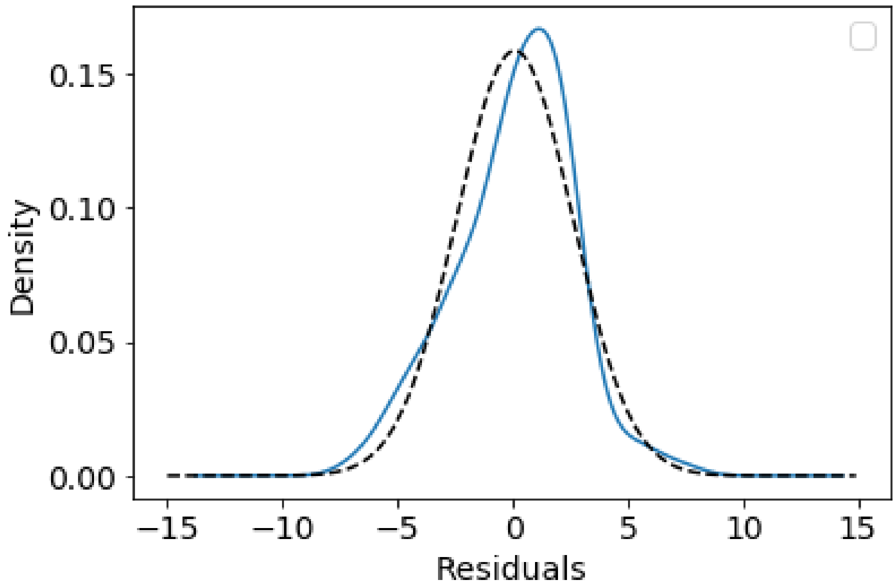


Fig. 9: Plot of the residual distribution and comparison with Gaussian distribution

to a gaussian distribution. Therefore, the residual is not skewed. *Hence, the model has a good fit.*

B Granger Causality Test

The Granger Causality Test has been performed to assess the causality of BTC & XRP Daily Transaction Volume on VIX Granger and VIX Granger on BTC & XRP Daily Transaction Volume up to four lags. Both of these tests show no significant causality. The parameters used to test causality of XRP daily volume on VIX Ganger are provided in Table 9.

In Table 10, no significant causality has been established of BTC Daily Transaction Volume on VIX Granger.

In Table 11, no significant causality has been established of VIX Granger on BTC Daily Transaction Volume.

In Table 12, no significant causality has been established of VIX Granger on BTC Daily Transaction Volume.

Lag = 1				
ssr based F test:	F=0.0550	p=0.8146	df_denom=512	df_num=1
ssr based chi2 test:	chi2=0.0554	p=0.8140	df=1	
likelihood ratio test:	chi2=0.0554	p=0.8140	df=1	
parameter F test:	F=0.0550	p=0.8146	df_denom=512	df_num=1
Lag = 2				
ssr based F test:	F=0.2724	p=0.7617	df_denom=509	df_num=2
ssr based chi2 test:	chi2=0.5501	p=0.7595	df=2	
likelihood ratio test:	chi2=0.5498	p=0.7596	df=2	
parameter F test:	F=0.2724	p=0.7617	df_denom=509	df_num=2
Lag = 3				
ssr based F test:	F=0.4111	p=0.7451	df_denom=506	df_num=3
ssr based chi2 test:	chi2=1.2503	p=0.7410	df=3	
likelihood ratio test:	chi2=1.2488	p=0.7413	df=3	
parameter F test:	F=0.4111	p=0.7451	df_denom=506	df_num=3
Lag = 4				
ssr based F test:	F=1.1195	p=0.3465	df_denom=503	df_num=4
ssr based chi2 test:	chi2=4.5583	p=0.3357	df=4	
likelihood ratio test:	chi2=4.5381	p=0.3381	df=4	
parameter F test:	F=1.1195	p=0.3465	df_denom=503	df_num=4

Table 9: Causality of XRP's Daily Tx Volume on VIX Granger

Lag = 1				
ssr based F test:	F=1.1787	p=0.2783	df_denom=361	df_num=1
ssr based chi2 test:	chi2=1.1885	p=0.2756	df=1	
likelihood ratio test:	chi2=1.1866	p=0.2760	df=1	
parameter F test:	F=1.1787	p=0.2783	df_denom=361	df_num=1
Lag = 2				
ssr based F test:	F=0.7601	p=0.4684	df_denom=358	df_num=2
ssr based chi2 test:	chi2=1.5415	p=0.4627	df=2	
likelihood ratio test:	chi2=1.5382	p=0.4634	df=2	
parameter F test:	F=0.7601	p=0.4684	df_denom=358	df_num=2
Lag = 3				
ssr based F test:	F=0.5410	p=0.6545	df_denom=355	df_num=3
ssr based chi2 test:	chi2=1.6551	p=0.6470	df=3	
likelihood ratio test:	chi2=1.6514	p=0.6478	df=3	
parameter F test:	F=0.5410	p=0.6545	df_denom=355	df_num=3
Lag = 4				
ssr based F test:	F=1.5771	p=0.1799	df_denom=352	df_num=4
ssr based chi2 test:	chi2=6.4696	p=0.1667	df=4	
likelihood ratio test:	chi2=6.4123	p=0.1704	df=4	
parameter F test:	F=1.5771	p=0.1799	df_denom=352	df_num=4

Table 10: Causality of BTC Daily Transaction Volume on VIX Granger

Lag = 1				
ssr based F test:	F=0.4432	p=0.5060	df_denom=361	df_num=1
ssr based chi2 test:	chi2=0.4469	p=0.5038	df=1	
likelihood ratio test:	chi2=0.4467	p=0.5039	df=1	
parameter F test:	F=0.4432	p=0.5060	df_denom=361	df_num=1
Lag = 2				
ssr based F test:	F=0.8063	p=0.4473	df_denom=358	df_num=2
ssr based chi2 test:	chi2=1.6351	p=0.4415	df=2	
likelihood ratio test:	chi2=1.6315	p=0.4423	df=2	
parameter F test:	F=0.8063	p=0.4473	df_denom=358	df_num=2
Lag = 3				
ssr based F test:	F=0.8249	p=0.4808	df_denom=355	df_num=3
ssr based chi2 test:	chi2=2.5235	p=0.4711	df=3	
likelihood ratio test:	chi2=2.5148	p=0.4726	df=3	
parameter F test:	F=0.8249	p=0.4808	df_denom=355	df_num=3
Lag = 4				
ssr based F test:	F=0.8720	p=0.4808	df_denom=352	df_num=4
ssr based chi2 test:	chi2=3.5771	p=0.4662	df=4	
likelihood ratio test:	chi2=3.5595	p=0.4689	df=4	
parameter F test:	F=0.8720	p=0.4808	df_denom=352	df_num=4

Table 11: Causality of VIX Granger on BTC Daily Transaction Volume

Lag = 1				
ssr based F test:	F=0.0050	p=0.9434	df_denom=512	df_num=1
ssr based chi2 test:	chi2=0.0051	p=0.9432	df=1	
likelihood ratio test:	chi2=0.0051	p=0.9432	df=1	
parameter F test:	F=0.0050	p=0.9434	df_denom=512	df_num=1
Lag = 2				
ssr based F test:	F=0.9214	p=0.3986	df_denom=509	df_num=2
ssr based chi2 test:	chi2=1.8609	p=0.3944	df=2	
likelihood ratio test:	chi2=1.8575	p=0.3950	df=2	
parameter F test:	F=0.9214	p=0.3986	df_denom=509	df_num=2
Lag = 3				
ssr based F test:	F=1.0486	p=0.3707	df_denom=506	df_num=3
ssr based chi2 test:	chi2=3.1892	p=0.3634	df=3	
likelihood ratio test:	chi2=3.1793	p=0.3648	df=3	
parameter F test:	F=1.0486	p=0.3707	df_denom=506	df_num=3
Lag = 4				
ssr based F test:	F=0.7670	p=0.5471	df_denom=503	df_num=4
ssr based chi2 test:	chi2=3.1228	p=0.5375	df=4	
likelihood ratio test:	chi2=3.1133	p=0.5390	df=4	
parameter F test:	F=0.7670	p=0.5471	df_denom=503	df_num=4

Table 12: Causality of VIX Granger on XRP Daily Transaction Volume