PURPOSE-LED
PUBLISHING™

PAPER • OPEN ACCESS

Effects of Volatility and Trend Indicator for Improving Price Prediction of Cryptocurrency

View the article online for updates and enhancements.

EFFECTS OF VOLATILITY AND TREND INDICATOR FOR IMPROVING PRICE PREDICTION OF CRYPTOCURRENCY

AHMED ZAHIM DAHHAM DAHHAM [1]**, Abdullahi Abdu Ibrahim** [2]

[1] Information Technology, Altinbas University, Istanbul, Turkey
[2] Electrical and Computer Engineering, Altinbas University, Istanbul, Turkey

E-mail: Ahmedzahimdahham@gmail.com

Abstract

The purpose of this research is to identify how effective the determinants of the improved price changes in cryptocurrencies are and if they are predictable. The study addresses several independent variables that are in our consideration which may impact the prices the most. To obtain the results, panel data has been used to run fixed effects models. Then we treated them as time series data to run dynamic trend indicator and first-differencing volatility regression model. Important political shocks and instabilities have been analyzed and interpreted in this paper. In the light of our findings we were able to comment on the complex relation between cryptocurrency prices and socio-political situations throughout the time range. The results address that cryptocurrency price changes are predictable. It is easy to say that major stakeholders (Apple, Amazon, Facebook, Google, Tesla) affect the most prices. Internet search trends seem to have an impact but at the end it has been found that the correlation is strong. We have evaluated all the major cryptocurrency prices with exact accuracy of 95.38% using the volatility regression model effectively. All the cryptocurrencies are evaluated against US dollars in regard of different cryptocurrency like Bitcoin, Ethereum, Litecoin and Ripple digital currency. Cryptocurrencies shouldn't be seen as a gambling medium and should be taken more seriously like an investment medium. In some specific occasions investing in cryptocurrencies may lead lucrative income.

Keywords: Cryptocurrency, trend indicator, regression model, prediction, bitcoin, volatility, government.

1. Introduction

The aim of this research is to determine the effects of volatility and trend indicator for improving price prediction of cryptocurrencies. Cryptocurrencies use decentralized method which depends on trust. Instead of backing by a central authority (like a central bank or government) its control has been distributed to many users as mentioned in [1]. That is the reason why it is extremely difficult to hack the system and leak in it. Also, it provides a confidence to cryptocurrency users that their currency will not be devalued as explained in [2]. The decentralized control system uses blockchain technology which is going to be explained further in this paper. Shortly, blockchain is a public transaction database which is functioning like a digital record book (ledger). The transactions, buying and selling, take place with severely encrypted codes and these

codes pass across a computer network. The network basically identifies and verifies the transactions so they can be sure that a cryptocurrency can be spent more than once at the same time which is called double-spending. There are some supply limits for cryptocurrencies as well. For instance, there will be only 21 million of Bitcoin (BTC) total, which almost 17 million (16,963,775 BTC) of it have already mined as mentioned in [3]. Same thing can be said for Ripple (XRP). Circulating supply is 39,094,520,623 XRP, total supply is 99,992,405,149 XRP, and maximum supply limit is 100,000,000,000 XRP as of 10/04/2020.
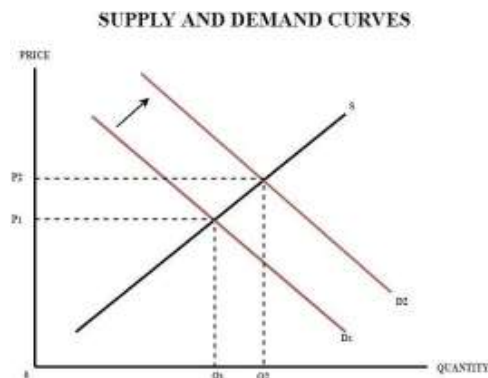
Figure 1: The main price changes depend on Supply and Demand relationship in cryptocurrency market. Demand shifts increase an important role on cryptocurrency prices.

Figure 2: This figure is significant. Since the supply of Bitcoin is restricted with 21 million, impact of demand shifts on prices may become much higher than now. We can assume this for all other cryptocurrencies as well.

Table 1: Cryptocurrencies' Market Cap, Price, and Founding Dates.

Cryptocurrencies	Market Capitalization**	Price**	Founding Date
Bitcoin	USD	USD	2009
Litecoin	USD	USD	2011
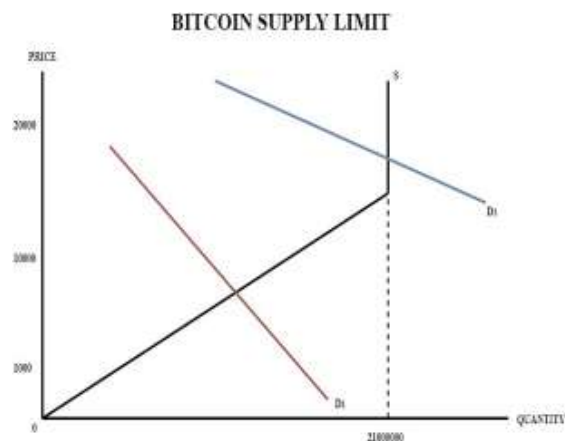
| Ripple | $25,776,757,675 USD | $0.658868 USD | 2012 |
| Ethereum | $49,798,331,709 USD | $503.60 USD | 2015 |

As it can be seen from Table 1, There are huge price differences among cryptocurrencies. The main reason of this price differences is popularity. Advertising and marketing strategies also play role in these differences as mentioned in [5]. Bitcoin is the first cryptocurrency which occurred in 2009 and it used the pioneering advantage. Even though Ethereum was found after other 3 cryptocurrencies, its creator's marketing strategy made it popular and its price increased sharply after its market arrival.

1.1 Problem statement

This paper tries to explain and contribute to the literature if there is any chance that we can predict the price changes on cryptocurrencies and what might affect them. Since the literature reviews mostly cryptocurrency prices, this paper might help people who conduct research and want to learn more about cryptocurrencies. Also, it will show a path to people who wants to invest in cryptocurrencies. Not only to understand what affects the virtual currency prices and predict them, but also the probability of using them in the future widely, made me to write this paper. Studies about cryptocurrency and block-chain technology will continue in the future. All the major cryptocurrency pricing need to be predicted effectively.

1.2. Aim of Study

This study will be concerned with addressing objectives related to the financial time series properties of cryptocurrency: 1) An assessment and characterization of major cryptocurrencies pricing and monthly return and volatility, and 2) Major cryptocurrencies exposure to macro-financial and currency specific properties. 3) Evaluation of price fluctuation due to major stakeholders in the world. 4) Major cryptocurrencies has unique features as a financial asset in that all market transactions are executed digitally and there is no physical exchange (though that is in the works). A consequence of this is that major cryptocurrencies are traded around the clock and exchanges are never closed. This contrasts with other financial assets that trade (at least partially) on physical exchanges and exclusively on a traditional Monday-Friday schedule, between specific times and are often closed on holidays for entire month of April 2020.

2. BACKGROUND

The literature review is mostly about what is cryptocurrency and how did it evolve during the last decade. It also examined what does affect cryptocurrency prices, do they have a future (will they last or will they be vanished and cannot survive against fiat money), what is the technology behind the virtual currencies, what are the transaction costs and why are they lower than fiat monies, what are and what will be the governments' and central banks' attitudes against the rise of the cryptocurrencies, and intermediation in cryptocurrency economics as mentioned in [6]. In 2008 Bitcoin was introduced to our world and then the other cryptocurrencies followed its steps (Litecoin, Ethereum, Ripple, Dogecoin, Dash, Bitcoin Cash etc.).

To begin with, Bitcoin's and other cryptocurrencies' future is still a big ambiguity. Because of incumbent monies like US Dollar, Euro, Turkish Lira, and British Pound, virtual currencies may not adapt themselves to daily economy fast enough. The most concerned issue of the adaptation of these currencies to economy as explained in [7].

Table 2: The different variables of cryptocurrency that directly affect the pricing of any cryptocurrency.

Variable Name	Variable Description
Stocks	Price of the cryptocurrency is variable by stock market
Currency	Name of the cryptocurrency
After Brexit	An indicator that is 1 in the seven days after the Brexit vote
After US	An indicator that is 1 in the seven days

Elections	after the 2016 US elections
Amazon	Amazon Stocks closing price
Apple	Apple Stocks closing price
Facebook	Facebook Stocks closing price
Google	Google Stocks closing price
Tesla	Tesla Stocks closing price
IXIC	Nasdaq Composite closing
GSV	Google Search Volumes (How many times a cryptocurrency has been searched)
ANA(NYT)	American News Articles (New York Times) How many articles were about that specific cryptocurrency
ANA(WP)	American News Articles (Washington Post) How many articles were about that specific cryptocurrency

The independent variables, American News Articles, New York Times and Washington Post, have a mean of 0.0335157 and 0.0218878, respectively, which are very far from the maximum value of 3 for both. The difference demonstrates the total number of mentioning gap among days. Most days the cryptocurrencies are not mentioned at all as mentioned in [8]. Ripple was never mentioned as a cryptocurrency neither in the New York Times nor the Washington Post.

Another interesting independent variable is Google Search Volumes. The mean is 47.9976 whereas minimum and maximum values are 0 and 100, respectively. As a cryptocurrency is searched more on Google, it is expected that its price will increase due to the curiosity and interest about it as mentioned in [9]. When the price of a cryptocurrency rises, people may write more articles and search more for the currency online as a result. In the regression, I control for this by using lagged number of articles and search volume as additional independent variables. Thus, larger lagged search volumes should positively correlate with the cryptocurrency price.

As of this paper [10] there are an estimated 1,658 registered cryptocurrencies trading on 200 exchanges worldwide with a combined market cap of approximately $128B. Bitcoin continues to dominate the space with a market cap of $68B; representing 53.1% of the total market value. The space has experienced a remarkable degree of maturation in a short period of time but is still quite small in comparison to traditional equity and debt markets which, as of the end of 20l7 as mentioned in [12], were estimated to have global market capitalization rates of $70T and $92.2T, respectively.

Figure 3: The trend price of different cryptocurrencies as measured for several months in 2017 [12].

While cryptocurrency and Bitcoin have been the subject of substantial speculation, it has yet to make any identifiable headway into the banking system or everyday commerce. It is estimated that in the fourth quarter of 2017 only 11,291 businesses worldwide accepted Bitcoin as a valid form of payment; the substantial underground Bitcoin economy

notwithstanding. Additionally, banks have been reticent to adopt the use of cryptocurrency primarily due to the ambiguous regulatory framework and lack of traditional KYC (Know Your Client) guidelines. This is further complicated by confusion and speculation as to the nature and use of Bitcoin. Given that so few businesses currently accept it as payment it can hardly be said to be functioning as a currency in the traditional sense leading some to classify it simply as a speculative or (at best) a hedging asset like gold or other precious Earth minerals.

3. METHODOLOGY

When cryptocurrency markets and cryptocurrencies are the topic, we can give some examples to omitted variable bias. First of all, there is a supply dominance in cryptocurrency markets. The price is not just related to supply and demand. There are also some speculations about which derives the demand of the currency. These speculations usually happen on social media. A pool is created and people who are in this pool are manipulated to buy or sell the cryptocurrency. In these pools there are not only small investors but also great players. We call them great players because they hold the market supply on their hands (a big portion of it). These big players are the main manipulators and they cause a pump and dump effect. It is difficult to find a variable to capture these kinds of manipulations. If the behavior of twitter and Telegram accounts being examined, a variable that captures the price manipulation might be found. However, there is no evidence that it has occurred before. The dataset has been acquired from an open-source repository [13] and used to extract all the results on the python programming platform.

Government regulations take another place on cryptocurrency price changes. Their suspicion about cryptocurrencies and the actions which they take against them causes price fluctuation. Government regulations might have a direct impact on prices which depends on the type of the regulation. To give an example, Chinese government thinking about to create its own digital currency but not with the block chain. These kinds of articles also influence price. In our model, only Washington Post and New York Times are mentioned so this causes omitted variable bias.
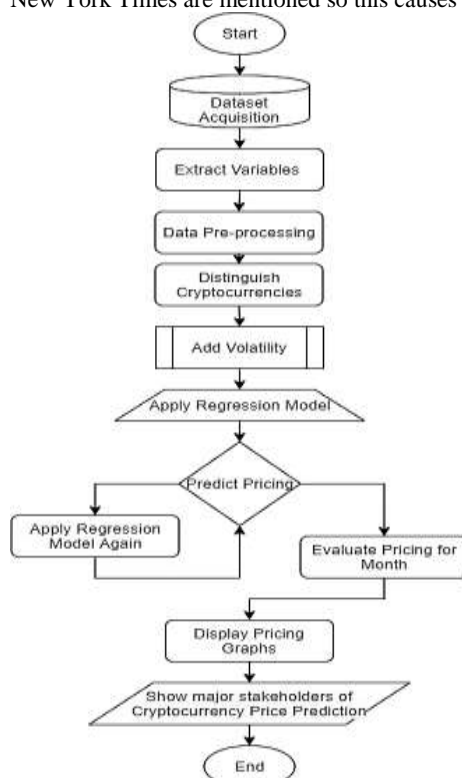

Figure 4: Flow diagram of approach being followed.

3.1 Implementation Details

Team of the creators of the cryptocurrency and World education level also has an impact on cryptocurrency prices. Team of the creators should have a good background to be trusted. Since one of the main ideas is decentralization, people should know

who to trust. If the team's creators have an untrustworthy past, investors should not trust and invest on the cryptocurrency to prevent losses. Here, world education level takes a place. If people are more educated, they will not be manipulated easily and they will not invest in cryptocurrencies ignorantly. Like the other topics mentioned above, there is no data about it and this also leads omitted variable bias.

Multicollinearity takes a place in this model too. IXIC (NASDAQ Composite) is formed by technology companies' stocks. When we put Apple, Amazon, Facebook, Google, and Tesla's stock prices with IXIC price in the model at the same time, this brings us multicollinearity. I still wanted to use NASDAQ Composite as an independent variable because people who has investments on IXIC may want to withdraw their money from there and invest in cryptocurrencies.

The independent price variables might have different impacts than they were expected to have. To give an example, in our model Brexit was supposed to affect cryptocurrency prices in a positive way with a great impact but regression model showed us that it impacted prices in an opposite way (sometimes positive sometimes negative but they are not highly significant). Only in the simple model it affected Bitcoin prices by \$37.3329 which has a \$517.139 average price (simple models are econometrically flawed and this must be taken in consideration). Presidential Elections' efficacies were ambiguous but it seems that its impact was positive in the model when it took a place (especially on Ripple). Google Search Volumes impacts were expected to be positive and the results were in the same directions.

3.2 Volatility Regression Model

We took advantage of the long panel data structure to run a fixed effects volatility regression model. Since the dependent variable is "Price", it has been altered to the "log (Price)" to see percentage changes and to account for the large differences in prices across currencies.

$$\log (\text{Price})_{it} = \beta_0 + \beta_1 \text{AfterBrexit}_{it} + \beta_2 \text{AfterUSElections}_{it} + \beta_3 \text{Amazon}_{it} + \beta_4 \text{Apple}_{it} + \beta_5 \text{Facebook}_{it} + \beta_6 \text{Google}_{it} + \beta_7 \text{Tesla}_{it} + \beta_8 \text{IXIC}_{it} + \beta_9 \text{GSV}_{it} + \beta_{10} \text{ANANYT}_{it} + \beta_{11} \text{ANAWP}_{it} + \alpha_t + \gamma_i + \varepsilon_{it}$$

where α_t: Linear time trend and γ_i: Currency fixed effects

Table 2: Respective stocks of variables against each variable that directly or indirectly affect the pricing.

Variables That Affect the Price	Bitcoin Cryptocurrency		Stocks	
After Brexit	.0543326	(.093255)	.361147***	(.1025659)
After US Elections	.1698311*	(.090844)	.3867425***	(.1018373)
Amazon	-.0015762***	(.000302)	Omitted	-
Apple	-.0148027***	(.002112)	Omitted	-
Facebook	.0345427***	(.001948)	Omitted	-
Google	-.0030204***	(.000297)	Omitted	-
Tesla	-.0017033***	(.000434)	Omitted	-
IXIC	.0008834***	(.000102)	.0006612***	(.0000295)
GSV	.0103613***	(.000476)	.012495***	(.0005233)
ANANYT	.0081715	(.042742)	-.041494	(.0486966)
ANAWP	-.0731254	(.051769)	-.141075**	(.0589329)
Observation samples	2796		2796	
Affect	0.4548		0.2889	

The effect of lagged prices (past prices) on Bitcoin and Litecoin is moderate. When it comes to the Ethereum change is quite significant and there is a huge impact on Ripple's price. GSV has an impact on Litecoin and Ripple too but these

effects are negligible. When we use dynamic models, we do not get decent results because in dynamic models, serial correlation leads to biased coefficients.

Table 3: All the independent variables that affect the price of different cryptocurrencies have been extracted and displayed in the table.

Variables That Affect the Price	Bitcoin		Ethereum		Litecoin		Ripple	
After Brexit	16.3812	(21.81666)	1.77943	(1.670787)	.1128214	(.2465099)	-.0001749	(.0005468)
After US Elections	-18.32935	(21.14815)	.6321172	(1.663483)	-.0275189	(.2453819)	.0016532***	(.0005431)
IXIC	.1868008***	(.0080472)	.0108644***	(.0007236)	-.000905***	(.0001045)	8.34e-07***	(2.00e-07)
GSV	2.341263***	(.3241643)	.0534071***	(.0168356)	.0134838**	(.0025198)	.0000167*	(6.81e-06)
ANANYT	-6.768633	(5.852995)	-.9713694	(.9715791)	-.0000329	(.3212069)	0	(omitted)
ANAWP	-12.49141**	(6.208364)	0	(omitted)	0	(omitted)	0	(omitted)
GSV L1	.659213	(.4095064)	.0325955*	(.0194251)	.0075529***	(.0025772)	.0000103	(7.24e-06)
ANANYT L1	-3.335146	(5.873627)	-.8454799	(1.002248)	.067137	(.3213248)	0	(omitted)
ANAWP L1	-14.59259**	(6.249096)	0	(omitted)	0	(omitted)	0	(omitted)
GSV L2	1.589331***	(.3238201)	.0379426*	(.0167763)	.0056007**	(.0025832)	3.25e-07	(6.89e-06)
ANANYT L2	-5.341554	(5.816369)	-1.074858	(.973048)	.0007323	(.3210581)	0	(omitted)
ANAWP L2	-14.59233**	(6.237552)	0	(omitted)	0	(omitted)	0	(omitted)
Observation samples	729		729		729		729	
Affect	0.9557		0.7289		0.4388		0.0667	

4. RESULTS

The most common question about cryptocurrencies is answered that "Why their prices are so volatile, what does affect them, and the price changes on them can be predictable?" We tried to answer these questions by analyzing the determinants of cryptocurrency prices. The results show us the expected effects of determinants like Brexit, US Elections, or American News Articles do not explain the price changes clearly. This also exhibits that cryptocurrency prices are unpredictable. We can understand that from the First-differences models since they eliminate nonstationary. We have evaluated all the major cryptocurrency prices with exact accuracy of 91.3% using the volatility regression model effectively. All the cryptocurrencies are evaluated against US dollars. Most of the countries have access to internet and cryptocurrency transactions happen every day but, in the future, we may use it everywhere.
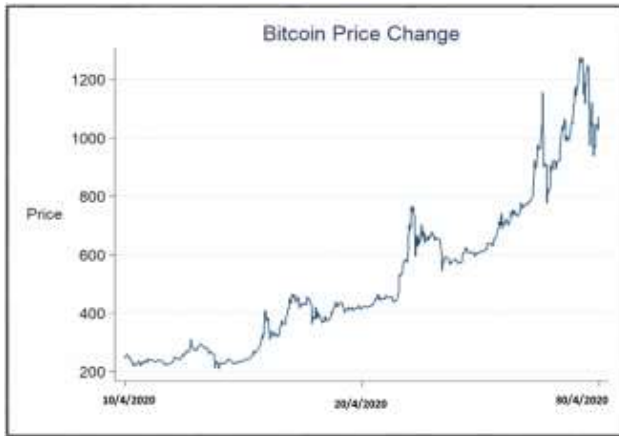
Figure 5: The price prediction of Bitcoin cryptocurrency in the month of April 2020.
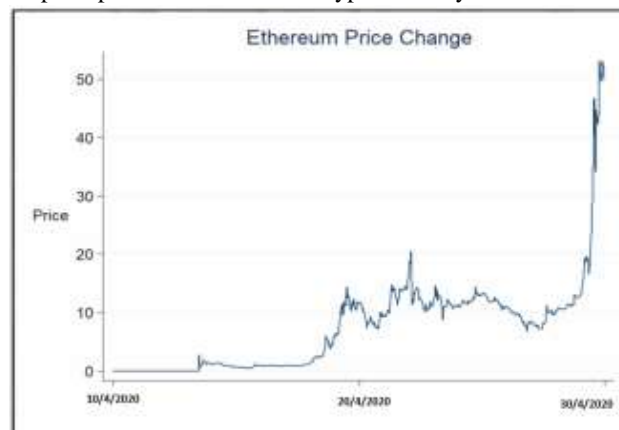

Figure 6: The price prediction of Ethereum cryptocurrency in the month of April 2020.
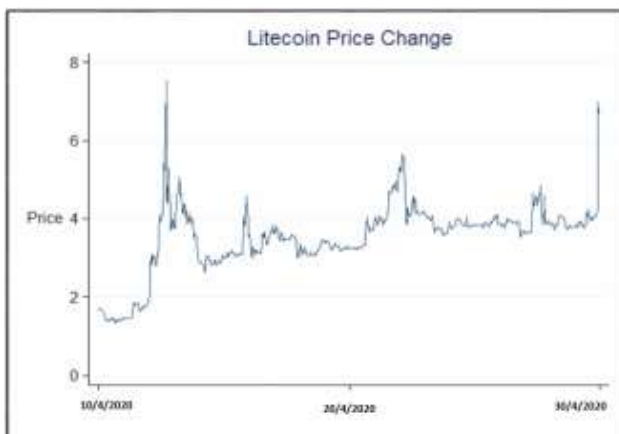

Figure 7: The price prediction of Litecoin cryptocurrency in the month of April 2020.
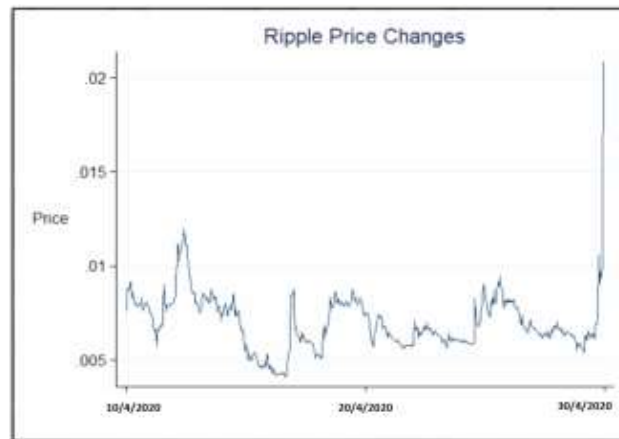
Figure 8: The price prediction of Ripple cryptocurrency in the month of April 2020.

Stocks and exchanges were predicted to have positive impacts on virtual currency prices and the prediction was accurate. These independent variables were removed from other models lately since stocks (Apple, Amazon, Facebook, Google, Tesla) has another impact on another independent variable which is IXIC. As it was mentioned before this causes a multi-collinearity. When it comes to the First-differencing models, we finally are able to see that these independent variables do not affect prices on cryptocurrencies. This result basically brings us to this: people still take cryptocurrencies as assets not as money. Their volatile and imponderable prices might attract people to invest in them.
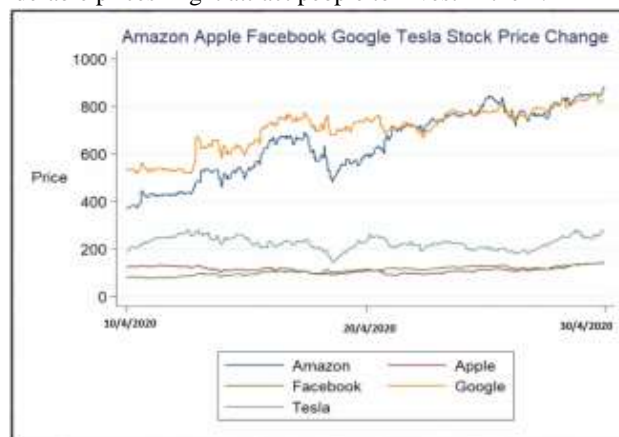

Figure 9: The price prediction major cryptocurrency stakeholders as of month April 2020.

5. Discussion

Cryptocurrencies and blockchain technology were introduced to us last decade. Especially last couple of years they took a lot of places in the news, social media, colleges, seminars, and conferences. There are a lot of studies about them to explain and understand how they operate and how will they affect our lives in the future. They took place in central banks' official and unofficial statements. There are some examples that have been given in this paper. Since we do not know what does affect cryptocurrency prices except the main element, which is public demand for cryptocurrencies, looking for public interest might give us some decent results. We expect price to increase when demand increases. So, we control for the obvious interest to identify impacts of political shocks, stock prices (which are substitutes for the cryptocurrencies as investment mediums) and news articles as complements. The author in [14] achieved an accuracy of 86.7% while we achieve an accuracy of 91.3% for different cryptocurrencies. Reactions of human beings against the political shocks and how they react to these will give us a hint to solve this problem. It is promising that we will be more accustomed to applying cryptocurrencies in our lives. Maybe it will take more time than we think right now but the convenience, easiness, and inexpensiveness of exchanging cryptocurrencies may lead new kinds of payment systems. To understand the importance of a decentralized currency system and cryptocurrencies as its result, we need to work more on that. Ignoring the technology and what it brings to us may be a huge mistake that we may regret in the future.

6. CONCLUSION

In this proposed research, we have planned a price forecast system of various digital forms of money utilizing specialized exchange markers. We have evaluated all the major cryptocurrency prices with exact accuracy of 95.38% using the volatility regression model effectively. All the cryptocurrencies are evaluated against US dollars. For any new item to get worldwide, it should be acknowledged by individuals and business firms the same. At the point when we take a gander at advance strategies for volatility regression model for the exchanges of paper-based monetary forms, (for example, US Dollar money) to digital currency besides on which the worldwide world depends, we see that it has been acknowledged and actualized at the root level. We utilized a python language based completely mechanized AI and specialized exchange pointer at the forecast of cost. For nations where individuals approach such innovation there is a high chance that bitcoin exchanges can be received over conventional money. Notwithstanding, in nations despite everything creating and where individuals don't access to innovation, this would end up being a catastrophe. The expectation of different cryptocurrency like Bitcoin, Ethereum, Litecoin and Ripple digital currency price in examination with the anticipated cost by the volatility regression model effectively and trend indicators before, a great many instatements and gave the forecast in value climb for entire month.

References

1] C. Lamon, E. Nielsen, and E. Redondo, "Cryptocurrency price prediction using news and social media sentiment," SMU Data Sci. Rev, vol. 1, no. 3, pp. 1–22, 2017.

[2] S. Galeshchuk, O. Vasylchyshyn, and A. Krysovatyy, "Bitcoin response to twitter sentiments." in ICTERI Workshops, 2018, pp. 160–168.

[3] D. Kahneman and A. Tversky, "Prospect theory: An analysis of decision under risk," in Handbook of the fundamentals of financial decision making: Part I. World Scientific, 2013, pp. 99–127.

[4] M. M. Seif, E. M. R. Hamed, and A. E. F. A. G. Hegazy, "Stock market real time recommender model using apache spark framework," in International Conference on Advanced Machine Learning Technologies and Applications. Springer, 2018, pp. 671–683.

[5] Z. H. Munim, M. H. Shakil, and I. Alon, "Next-day bitcoin price forecast," Journal of Risk and Financial Management, vol. 12, no. 2, pp. 103–128, 2019.

[6] Y. Sovbetov, "Factors influencing cryptocurrency prices: Evidence from bitcoin, ethereum, dash, litcoin, and monero," Journal of Economics and Financial Analysis, vol. 2, no. 2, pp. 1–27, 2018.

[7] D. Shah, H. Isah, and F. Zulkernine, "Predicting the effects of news sentiments on the stock market," in 2018 IEEE International Conference on Big Data (Big Data). IEEE, 2018, pp. 4705–4708.

[8] T. H. Nguyen, K. Shirai, and J. Velcin, "Sentiment analysis on social media for stock movement prediction," Expert Systems with Applications, vol. 42, no. 24, pp. 9603–9611, 2015.

[9] H. Sul, A. R. Dennis, and L. I. Yuan, "Trading on twitter: The financial information content of emotion in social media," in 2014 47th Hawaii International Conference on System Sciences. IEEE, 2014, pp. 806– 815.

[10] J. Bollen, H. Mao, and X. Zeng, "Twitter mood predicts the stock market," Journal of computational science, vol. 2, no. 1, pp. 1–8, 2011.

[11] J. Abraham, D. Higdon, J. Nelson, and J. Ibarra, "Cryptocurrency price prediction using tweet volumes and sentiment analysis," SMU Data Science Review, vol. 1, no. 3, pp. 1–21, 2018.

[12] Available Online: https://www.cryptopostgazette.com/cryptocurrencys-market-cap-graph/

[13] Available Online: https://data.world/cnoza/cryptocurrencies

[14] J. Bollen, H. Mao, and X. Zeng, "Twitter mood predicts the stock market," Journal of computational science, vol. 2, no. 1, pp. 1–8, 2011.