Analyzing The Effect of Social Media Activity on The Performance of Cryptocurrencies

Project Group 6

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INTRODUCTION

- A cryptocurrency (or “crypto”) is a digital currency that can be used to buy goods and services but uses an online ledger with strong cryptography to secure online transactions.
- Cryptocurrencies work using a technology called blockchain.
- Blockchain is a decentralized technology spread across many computers that manages and records transactions.
- Nearly 15,000 different cryptocurrencies are traded publicly, according to CoinMarketCap.com, a market research website.
- In recent times, it is observed that, out of all the factors, social media and internet are the ones which affect the functioning of these cryptocurrencies the most.

INTRODUCTION

- Particularly, we are interested in analyzing the effect of social media activities on the performance of cryptocurrencies Bitcoin and Ethereum.
- Bitcoin(BTC) is a digital or virtual currency created in 2009 that uses peer-to-peer technology to facilitate instant payments.
- According to a recent survey, more than 2,300 US businesses accept Bitcoin, one of the most popular cryptocurrencies[1].
- Ethereum (ETH) is the second most popular cryptocurrency after Bitcoin(BTC). As the second-largest cryptocurrency by market capitalization (market cap).
- Both of these tokens are decentralized, meaning that they are not issued or regulated by a central bank or other authority.

[1] https://www2.deloitte.com/us/en/pages/audit/articles/corporates-using-crypto.html

OBJECTIVES

By scraping a dataset through Twitter we plan to answer these research questions:

1. Does the nature of statement (positive, negative, or neutral) obtained from the social media affect the price trend of cryptocurrency?

    a. One of our goals in this project is to see whether the tweets related to cryptocurrencies affects the price trends of crypto or not?
    b. We want to analyze if a positive or negative tweet leads to an increase or decrease respectively in the price of the crypto or not?

1. Can we predict future cryptocurrency price trends based on current social media presence?

    a. Our goal for this question would be to try and predict whether the crypto has an upward or downward trend based on all the previous trends observed for the cryptocurrency.

TECHNIQUES USED

- **Web Scraping**-
  Tweets containing Bitcoin and Ethereum keywords are scraped from twitter using Snscrape.

- **Sentiment Analysis of tweets**-
  Using sentiment analyzers like VADER, Harvard's General Inquirer and Loughran-McDonald.

- **Time-Series Granularity**-
  Aggregating time-series of tweet sentiment and crypto price for both Bitcoin and Ethereum.

- **Vector Autoregression**-
  This autoregression is used when there are multiple time-series involved which are interdependent

DATA SOURCES & DESCRIPTION

- Two cryptocurrencies are taken into consideration, ‘Bitcoin’ and ‘Ethereum’.
- Snscrape is used to scrape tweets related to the two currencies using ‘Bitcoin’ and ‘Ethereum’ as keywords.
- Bitcoin and Ethereum each have 44,000 tweets scraped covering 89 days from 9/1/2021 to 11/29/2021 with 500 tweets being scrapped for each day.
- Equivalent historic prices for respective cryptocurrencies are also taken from Coindesk.com.

DATA PREPROCESSING

- Removed Signs- Removing of @, blank space and hashtags (#)
- Removed Punctuations
- Eliminating stop words
- Tokenization- Using nltk.word_tokenizer()
- Lemmatization- Using WordNetLemmitizer

SENTIMENT ANALYSIS

Sentiment analysis often relies on lists of words and phrases with positive and negative connotations. In this research, we used 3 different sentiment analysis methods:

- Vader Sentiment Analysis
  Vader (Valence Aware Dictionary for Sentiment Reasoning) is a model used for text sentiment analysis that is sensitive to polarity (positive/negative/neutral) and intensity (strength) of emotion.

- Harvard's General Inquirer
  A computer-assisted dictionary based approach for sentiment analysis of textual data. This is a general-purpose dictionary developed by the Harvard University.

- Loughran-McDonald
  Dictionary used to determine which tokens (collections of characters) are classified as words. Also includes sentiment word classifications.

Further, we compared the results for these methods and took the best result to train our VAR model.

Results for VADER sentiment analysis

	sentiment	Cleantext_lemmatized
1	Neutral	25030
2	Positive	13435
0	Negative	5535

BITCOIN RESULTS

	sentiment	Cleantext_lemmatized
1	Neutral	26872
2	Positive	12475
0	Negative	4653

ETHEREUM RESULTS

As you can see the results above, for both Bitcoin and Ethereum tweets , the results were similar, more number of tweets were neutral and a similar distribution for positive and negative tweets.

Further, other methods showed similar sentiment analysis results, we used these results and moved to the next part of our project

GRANULARITY/ TIME-SERIES

- **<u>Granularity</u>**-

  For our analysis, we have decided to aggregate our time-series per day i.e. the granularity is day.

- **<u>Bitcoin and Ethereum price</u>**-

  We downloaded historic crypto price with per day granularity. Along with closing price, volume and return is also present in data.

- **<u>Twitter data</u>**-

  Tweets retrieved were spread across the entire day. After sentiment analysis is performed, the resultant time-series is aggregate per day by using resampling.

TIMESERIES

- This is the final time-series we obtained after aggregating data for Bitcoin
- This includes date, score, closing price, returns and volume for each day.
- We then loaded this time series into the VAR model to get our results.
- A similar time-series with same variables was made for Ethereum as well.

	Date	score	Close	Bit_retrrn	Volume
0	9/1/2021	0.3612	48847.02734	0.035006	3.913940e+10
1	9/2/2021	0.0000	49327.72266	0.009793	3.950807e+10
2	9/3/2021	0.0000	50025.37500	0.014044	4.320618e+10
3	9/4/2021	-0.6249	49944.62500	-0.001615	3.747133e+10
4	9/5/2021	0.0000	51753.41016	0.035575	3.032268e+10
...	...	...	...	...	...
83	11/25/2021	-0.1280	57274.67969	0.017512	3.428402e+10
84	11/26/2021	0.8316	53569.76563	-0.066874	4.181075e+10
85	11/27/2021	0.1027	54815.07813	0.022980	3.056086e+10
86	11/28/2021	0.0000	57248.45703	0.043435	2.811689e+10
87	11/29/2021	0.1027	57806.56641	0.009702	3.237084e+10

VECTOR AUTOREGRESSION(VAR)

- Vector autoregression (VAR) is a statistical model used to capture the relationship between multiple quantities (Time Series) as they change over time. VAR is a type of stochastic process model.

- VAR models generalize the single-variable (univariate) autoregressive model by allowing for multivariate time series.

- Like the autoregressive model, each variable has an equation, modelling its evolution over time. This equation includes the variable's lagged (past) values, the lagged values of the other variables in the model, and an error term.

$$y_{1,t} = c_1 + a_{1,1}y_{1,t-1} + a_{1,2}y_{2,t-1} + e_{1,t}$$

$$y_{2,t} = c_2 + a_{2,1}y_{1,t-1} + a_{2,2}y_{2,t-1} + e_{2,t}$$

STATIONARITY AND DIFFERENCING

- Using non-stationary time series data in financial models produces unreliable and spurious results and leads to poor understanding and forecasting.

- A stationary time series is one whose properties do not depend on the time at which the series is observed.

- The **Dickey-Fuller** test is a way to determine whether a stochastic process has a unit root. If it has a unit root means it is non-stationary. The Augmented Dickey Fuller (ADF) test can handle more complex models than the Dickey-Fuller test, and it is more powerful.

- one way to make a non-stationary time series stationary is to compute the differences between consecutive observations. This is known as differencing.

LAG LENGTH SELECTION USING INFORMATION CRITERIA

- The selection of lag lengths in AR models can sometimes be challenging. Too many lags inflate the standard errors of coefficient estimates and thus imply an increase in the forecast error while omitting lags that should be included in the model may result in an estimation bias.

- There are statistical methods that are helpful to determine how many lags should be included as regressors.

- To circumvent the issue of producing too large models, one may choose the lag order (p) that minimizes the Akaike information criterion (AIC):

$$AIC(p) = \log\left(\frac{SSR(p)}{T}\right) + (p+1)\frac{2}{T}$$

Check Stationarity for BTC-Harvard Time Series

Bitcoin return time series

```
Augmented Dickey-Fuller Test:
ADF test statistic      -7.966448e+00
p-value                  2.856477e-12
# lags used              1.000000e+00
# observations           8.600000e+01
critical value (1%)     -3.508783e+00
critical value (5%)     -2.895784e+00
critical value (10%)    -2.585038e+00
Strong evidence against the null hypothesis
Reject the null hypothesis
Data has no unit root and is stationary
```

Bitcoin volume time series

```
Augmented Dickey-Fuller Test:
ADF test statistic      -5.357471
p-value                  0.000004
# lags used              3.000000
# observations          84.000000
critical value (1%)     -3.510712
critical value (5%)     -2.896616
critical value (10%)    -2.585482
Strong evidence against the null hypothesis
Reject the null hypothesis
Data has no unit root and is stationary
```

Bitcoin Harvard Positive time series

```
Augmented Dickey-Fuller Test:
ADF test statistic      -9.071912e+00
p-value                  4.279510e-15
# lags used              0.000000e+00
# observations           8.700000e+01
critical value (1%)     -3.507853e+00
critical value (5%)     -2.895382e+00
critical value (10%)    -2.584824e+00
Strong evidence against the null hypothesis
Reject the null hypothesis
Data has no unit root and is stationary
```

Bitcoin Harvard Negative time series

```
ADF test statistic      -9.354055e+00
p-value                  8.149060e-16
# lags used              0.000000e+00
# observations           8.700000e+01
critical value (1%)     -3.507853e+00
critical value (5%)     -2.895382e+00
critical value (10%)    -2.584824e+00
Strong evidence against the null hypothesis
Reject the null hypothesis
Data has no unit root and is stationary
```

Bitcoin Harvard Polarity time series

```
Augmented Dickey-Fuller Test:
ADF test statistic      -6.855801e+00
p-value                  1.649723e-09
# lags used              0.000000e+00
# observations           8.700000e+01
critical value (1%)     -3.507853e+00
critical value (5%)     -2.895382e+00
critical value (10%)    -2.584824e+00
Strong evidence against the null hypothesis
Reject the null hypothesis
Data has no unit root and is stationary
```

Bitcoin Harvard Subjectivity time series

```
Augmented Dickey-Fuller Test:
ADF test statistic      -8.681716e+00
p-value                  4.268366e-14
# lags used              0.000000e+00
# observations           8.700000e+01
critical value (1%)     -3.507853e+00
critical value (5%)     -2.895382e+00
critical value (10%)    -2.584824e+00
Strong evidence against the null hypothesis
Reject the null hypothesis
Data has no unit root and is stationary
```

Check Stationarity for BTC-LM Time Series

Bitcoin return time series

```
Augmented Dickey-Fuller Test:
ADF test statistic      -7.966448e+00
p-value                  2.856477e-12
# lags used              1.000000e+00
# observations           8.600000e+01
critical value (1%)     -3.508783e+00
critical value (5%)     -2.895784e+00
critical value (10%)    -2.585038e+00
Strong evidence against the null hypothesis
Reject the null hypothesis
Data has no unit root and is stationary
```

Bitcoin volume time series

```
Augmented Dickey-Fuller Test:
ADF test statistic      -5.357471
p-value                  0.000004
# lags used              3.000000
# observations          84.000000
critical value (1%)     -3.510712
critical value (5%)     -2.896616
critical value (10%)    -2.585482
Strong evidence against the null hypothesis
Reject the null hypothesis
Data has no unit root and is stationary
```

Bitcoin LM Positive time series

```
Augmented Dickey-Fuller Test:
ADF test statistic      -9.071912e+00
p-value                  4.279510e-15
# lags used              0.000000e+00
# observations           8.700000e+01
critical value (1%)     -3.507853e+00
critical value (5%)     -2.895382e+00
critical value (10%)    -2.584824e+00
Strong evidence against the null hypothesis
Reject the null hypothesis
Data has no unit root and is stationary
```

Bitcoin LM Negative time series

```
ADF test statistic      -9.354055e+00
p-value                  8.149060e-16
# lags used              0.000000e+00
# observations           8.700000e+01
critical value (1%)     -3.507853e+00
critical value (5%)     -2.895382e+00
critical value (10%)    -2.584824e+00
Strong evidence against the null hypothesis
Reject the null hypothesis
Data has no unit root and is stationary
```

Bitcoin LM Polarity time series

```
Augmented Dickey-Fuller Test:
ADF test statistic      -6.855801e+00
p-value                  1.649723e-09
# lags used              0.000000e+00
# observations           8.700000e+01
critical value (1%)     -3.507853e+00
critical value (5%)     -2.895382e+00
critical value (10%)    -2.584824e+00
Strong evidence against the null hypothesis
Reject the null hypothesis
Data has no unit root and is stationary
```

Bitcoin LM Subjectivity time series

```
Augmented Dickey-Fuller Test:
ADF test statistic      -8.681716e+00
p-value                  4.268366e-14
# lags used              0.000000e+00
# observations           8.700000e+01
critical value (1%)     -3.507853e+00
critical value (5%)     -2.895382e+00
critical value (10%)    -2.584824e+00
Strong evidence against the null hypothesis
Reject the null hypothesis
Data has no unit root and is stationary
```

Check Stationarity for Eth-Harvard Time Series

Ethereum return time series

```
Augmented Dickey-Fuller Test:
ADF test statistic     -7.966448e+00
p-value                 2.856477e-12
# lags used             1.000000e+00
# observations          8.600000e+01
critical value (1%)    -3.508783e+00
critical value (5%)    -2.895784e+00
critical value (10%)   -2.585038e+00
Strong evidence against the null hypothesis
Reject the null hypothesis
Data has no unit root and is stationary
```

Ethereum volume time series

```
Augmented Dickey-Fuller Test:
ADF test statistic     -5.357471
p-value                 0.000004
# lags used             3.000000
# observations         84.000000
critical value (1%)    -3.510712
critical value (5%)    -2.896616
critical value (10%)   -2.585482
Strong evidence against the null hypothesis
Reject the null hypothesis
Data has no unit root and is stationary
```

Ethereum Harvard Positive time series

```
Augmented Dickey-Fuller Test:
ADF test statistic     -9.071912e+00
p-value                 4.279510e-15
# lags used             0.000000e+00
# observations          8.700000e+01
critical value (1%)    -3.507853e+00
critical value (5%)    -2.895382e+00
critical value (10%)   -2.584824e+00
Strong evidence against the null hypothesis
Reject the null hypothesis
Data has no unit root and is stationary
```

Ethereum Harvard Negative time series

```
Augmented Dickey-Fuller Test:
ADF test statistic     -2.590939
p-value                 0.094884
# lags used             4.000000
# observations         83.000000
critical value (1%)    -3.511712
critical value (5%)    -2.897048
critical value (10%)   -2.585713
Weak evidence against the null hypothesis
Fail to reject the null hypothesis
Data has a unit root and is non-stationary
```

Ethereum Harvard Polarity time series

```
Augmented Dickey-Fuller Test:
ADF test statistic     -1.927852
p-value                 0.319074
# lags used             7.000000
# observations         80.000000
critical value (1%)    -3.514869
critical value (5%)    -2.898409
critical value (10%)   -2.586439
Weak evidence against the null hypothesis
Fail to reject the null hypothesis
Data has a unit root and is non-stationary
```

Ethereum Harvard Subjectivity time series

```
Augmented Dickey-Fuller Test:
ADF test statistic     -2.133462
p-value                 0.231274
# lags used             4.000000
# observations         83.000000
critical value (1%)    -3.511712
critical value (5%)    -2.897048
critical value (10%)   -2.585713
Weak evidence against the null hypothesis
Fail to reject the null hypothesis
Data has a unit root and is non-stationary
```

Check Stationarity for Eth-LM Time Series

Bitcoin return time series

```
Augmented Dickey-Fuller Test:
ADF test statistic      -7.966448e+00
p-value                  2.856477e-12
# lags used              1.000000e+00
# observations           8.600000e+01
critical value (1%)     -3.508783e+00
critical value (5%)     -2.895784e+00
critical value (10%)    -2.585038e+00
Strong evidence against the null hypothesis
Reject the null hypothesis
Data has no unit root and is stationary
```

Bitcoin volume time series

```
Augmented Dickey-Fuller Test:
ADF test statistic      -5.357471
p-value                  0.000004
# lags used              3.000000
# observations          84.000000
critical value (1%)     -3.510712
critical value (5%)     -2.896616
critical value (10%)    -2.585482
Strong evidence against the null hypothesis
Reject the null hypothesis
Data has no unit root and is stationary
```

Bitcoin Harvard Positive time series

```
Augmented Dickey-Fuller Test:
ADF test statistic      -9.071912e+00
p-value                  4.279510e-15
# lags used              0.000000e+00
# observations           8.700000e+01
critical value (1%)     -3.507853e+00
critical value (5%)     -2.895382e+00
critical value (10%)    -2.584824e+00
Strong evidence against the null hypothesis
Reject the null hypothesis
Data has no unit root and is stationary
```

Bitcoin Harvard Negative time series

```
ADF test statistic      -9.354055e+00
p-value                  8.149060e-16
# lags used              0.000000e+00
# observations           8.700000e+01
critical value (1%)     -3.507853e+00
critical value (5%)     -2.895382e+00
critical value (10%)    -2.584824e+00
Strong evidence against the null hypothesis
Reject the null hypothesis
Data has no unit root and is stationary
```

Bitcoin Harvard Polarity time series

```
Augmented Dickey-Fuller Test:
ADF test statistic      -6.855801e+00
p-value                  1.649723e-09
# lags used              0.000000e+00
# observations           8.700000e+01
critical value (1%)     -3.507853e+00
critical value (5%)     -2.895382e+00
critical value (10%)    -2.584824e+00
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Reject the null hypothesis
Data has no unit root and is stationary
```

Bitcoin Harvard Subjectivity time series

```
Augmented Dickey-Fuller Test:
ADF test statistic      -8.681716e+00
p-value                  4.268366e-14
# lags used              0.000000e+00
# observations           8.700000e+01
critical value (1%)     -3.507853e+00
critical value (5%)     -2.895382e+00
critical value (10%)    -2.584824e+00
Strong evidence against the null hypothesis
Reject the null hypothesis
Data has no unit root and is stationary
```

Choosing the order of Vector Autoregression

Bitcoin Harvard	Bitcoin LM	Ethereum Harvard	Ethereum LM
Order = 1 AIC: 11.213565069590262	Order = 1 AIC: 12.623249894047625	Order = 1 AIC: 11.213565069590262	Order = 1 AIC: 12.623249894047625
Order = 2 AIC: 11.483064822910013	Order = 2 AIC: 12.623249894047625	Order = 2 AIC: 11.483064822910013	Order = 2 AIC: 12.623249894047625
Order = 3 AIC: 12.085883071223611	Order = 3 AIC: 12.623249894047625	Order = 3 AIC: 12.085883071223611	Order = 3 AIC: 12.623249894047625
Order = 4 AIC: 12.470018792093143	Order = 4 AIC: 12.623249894047625	Order = 4 AIC: 12.470018792093143	Order = 4 AIC: 12.623249894047625
Order = 5 AIC: 12.623249894047625	Order = 5 AIC: 12.623249894047625	Order = 5 AIC: 12.623249894047625	Order = 5 AIC: 12.623249894047625

Result of VAR for Bit - Harvard

Results for equation Bit_return

	coefficient	std. error	t-stat	prob
const	-0.043227	0.063916	-0.676	0.499
L1.Bit_return	0.041814	0.111980	0.373	0.709
L1.Volume	0.000000	0.000000	0.039	0.969
L1.Positive_Har_Bit	-0.007480	0.089287	-0.084	0.933
L1.Negative_Har_Bit	0.166998	0.131043	1.274	0.203
L1.Polarity_Har_Bit	0.002034	0.202470	0.010	0.992
L1.Subjectivity_Har_Bit	-0.224355	0.548918	-0.409	0.683

Results for equation Volume

	coefficient	std. error	t-stat	prob
const	25658946329.289799	11084613575.477999	2.315	0.021
L1.Bit_return	-12273988075.592810	19420098317.677277	-0.632	0.527
L1.Volume	0.312121	0.107900	2.893	0.004
L1.Positive_Har_Bit	-6784151231.178294	15484530712.315434	-0.438	0.661
L1.Negative_Har_Bit	-27094355080.761982	22726013684.923401	-1.192	0.233
L1.Polarity_Har_Bit	3695099344.851302	35113240914.591949	0.105	0.916
L1.Subjectivity_Har_Bit	132313720287.804535	95195830056.517563	1.390	0.165

Results for equation Positive_Har_Bit

	coefficient	std. error	t-stat	prob
const	0.824123	0.177942	4.631	0.000
L1.Bit_return	0.070643	0.311752	0.227	0.821
L1.Volume	0.000000	0.000000	2.037	0.042
L1.Positive_Har_Bit	0.043443	0.248574	0.175	0.861
L1.Negative_Har_Bit	-0.298666	0.364822	-0.819	0.413
L1.Polarity_Har_Bit	-0.067724	0.563674	-0.120	0.904
L1.Subjectivity_Har_Bit	1.862921	1.528183	1.219	0.223

Results for equation Negative_Har_Bit

	coefficient	std. error	t-stat	prob
const	0.559559	0.106139	5.272	0.000
L1.Bit_return	-0.121823	0.185954	-0.655	0.512
L1.Volume	0.000000	0.000000	1.178	0.239
L1.Positive_Har_Bit	-0.051436	0.148270	-0.347	0.729
L1.Negative_Har_Bit	0.083989	0.217609	0.386	0.700
L1.Polarity_Har_Bit	-0.062034	0.336221	-0.185	0.854
L1.Subjectivity_Har_Bit	-0.376766	0.911532	-0.413	0.679

Results for equation Polarity_Har_Bit

	coefficient	std. error	t-stat	prob
const	0.073355	0.073054	1.004	0.315
L1.Bit_return	0.018648	0.127989	0.146	0.884
L1.Volume	0.000000	0.000000	1.218	0.223
L1.Positive_Har_Bit	0.003470	0.102051	0.034	0.973
L1.Negative_Har_Bit	-0.149331	0.149777	-0.997	0.319
L1.Polarity_Har_Bit	0.198534	0.231415	0.858	0.391
L1.Subjectivity_Har_Bit	1.002855	0.627392	1.598	0.110

Results for equation Subjectivity_Har_Bit

	coefficient	std. error	t-stat	prob
const	0.132599	0.018575	7.139	0.000
L1.Bit_return	-0.026123	0.032543	-0.803	0.422
L1.Volume	0.000000	0.000000	1.721	0.085
L1.Positive_Har_Bit	0.001375	0.025948	0.053	0.958
L1.Negative_Har_Bit	-0.001267	0.038083	-0.033	0.973
L1.Polarity_Har_Bit	-0.008382	0.058841	-0.142	0.887
L1.Subjectivity_Har_Bit	0.059720	0.159525	0.374	0.708

Result of VAR for Eth - Harvard

Results for equation Eth_return

	coefficient	std. error	t-stat	prob
const	-0.008239	0.060822	-0.135	0.892
L1.Eth_return	-0.003011	0.111437	-0.027	0.978
L1.Volume	0.000000	0.000000	0.968	0.333
L1.Positive_Har_Eth	-0.006218	0.115608	-0.054	0.957
L1.Negative_Har_Eth	0.098315	0.154575	0.636	0.525
L1.Polarity_Har_Eth	-0.028208	0.219211	-0.129	0.898
L1.Subjectivity_Har_Eth	-0.390807	0.742856	-0.526	0.599

Results for equation Volume

	coefficient	std. error	t-stat	prob
const	11394114401.450384	5609189623.554939	2.031	0.042
L1.Eth_return	-5507457108.226655	10277044908.254744	-0.536	0.592
L1.Volume	0.391412	0.106145	3.688	0.000
L1.Positive_Har_Eth	5981064239.300002	10661705141.460880	0.561	0.575
L1.Negative_Har_Eth	-7402437011.808105	14255412457.761545	-0.519	0.604
L1.Polarity_Har_Eth	-20899689805.725441	20216389999.574188	-1.034	0.301
L1.Subjectivity_Har_Eth	18281784517.799839	68508558390.861389	0.267	0.790

Results for equation Positive_Har_Eth

	coefficient	std. error	t-stat	prob
const	0.822305	0.133225	6.172	0.000
L1.Eth_return	-0.128668	0.244091	-0.527	0.598
L1.Volume	0.000000	0.000000	0.855	0.392
L1.Positive_Har_Eth	0.327810	0.253228	1.295	0.195
L1.Negative_Har_Eth	-0.357503	0.338582	-1.056	0.291
L1.Polarity_Har_Eth	-0.601828	0.480162	-1.253	0.210
L1.Subjectivity_Har_Eth	0.772632	1.627156	0.475	0.635

Results for equation Negative_Har_Eth

	coefficient	std. error	t-stat	prob
const	0.419701	0.077527	5.414	0.000
L1.Eth_return	-0.164569	0.142044	-1.159	0.247
L1.Volume	0.000000	0.000000	0.518	0.604
L1.Positive_Har_Eth	-0.004084	0.147360	-0.028	0.978
L1.Negative_Har_Eth	0.156152	0.197031	0.793	0.428
L1.Polarity_Har_Eth	0.149943	0.279420	0.537	0.592
L1.Subjectivity_Har_Eth	-0.354265	0.946889	-0.374	0.708

Results for equation Polarity_Har_Eth

	coefficient	std. error	t-stat	prob
const	0.173040	0.064709	2.674	0.007
L1.Eth_return	-0.087170	0.118558	-0.735	0.462
L1.Volume	0.000000	0.000000	0.797	0.425
L1.Positive_Har_Eth	0.100063	0.122995	0.814	0.416
L1.Negative_Har_Eth	-0.283962	0.164453	-1.727	0.084
L1.Polarity_Har_Eth	-0.282768	0.233220	-1.212	0.225
L1.Subjectivity_Har_Eth	0.779168	0.790326	0.986	0.324

Results for equation Subjectivity_Har_Eth

	coefficient	std. error	t-stat	prob
const	0.105505	0.014220	7.419	0.000
L1.Eth_return	-0.024761	0.026054	-0.950	0.342
L1.Volume	0.000000	0.000000	2.512	0.012
L1.Positive_Har_Eth	0.006359	0.027029	0.235	0.814
L1.Negative_Har_Eth	-0.065392	0.036139	-1.809	0.070
L1.Polarity_Har_Eth	-0.073611	0.051251	-1.436	0.151
L1.Subjectivity_Har_Eth	0.368487	0.173679	2.122	0.034

CONCLUSION

- Our results showed that there is no significant relation between Bitcoin price and sentiment analysis result.
- Our results showed that there is no significant relation between volume of trade of Bitcoin and sentiment analysis result.
- Our results showed that there is no significant relation between ethereum price and sentiment analysis result.
- Our results showed that there is no significant relation between volume of trade of ethereum and sentiment analysis result.

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THANK YOU