What Drives Cryptocurrency Prices? An Investigation of Google Trends and Telegram Sentiment

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ABSTRACT

The Google Trends[1] search analysis service and the Telegram[2] messaging platform are investigated to determine their respective relationships to cryptocurrency price behaviour. It is shown that, in contrast to earlier findings, the relationship between cryptocurrency price movements and internet search volumes obtained from Google Trends is no longer consistently positive, with strong negative correlations detected for Bitcoin and Ethereum during June 2018. Sentiment extracted from cryptocurrency investment groups on Telegram is found to be positively correlated to Bitcoin and Ethereum price movements, particularly during periods of elevated volatility. The number of messages posted on a Bitcoin-themed Telegram group is found to be an indicator of Bitcoin price action in the subsequent week. A long short-term memory (LSTM) recurrent neural network is developed to predict the direction of cryptocurrency prices using data obtained from Google Trends and Telegram. It is shown that Telegram data is a better predictor of the direction of the Bitcoin market than Google Trends. The converse is true for Ethereum. The LSTM model produces the most accurate results when predicting price movements over a one-week period.

Categories and Subject Descriptors

[**Applied Computing**]: Operations Research—*Forecasting*

Keywords

Cryptocurrency, sentiment, Bitcoin, Ethereum, Telegram, Google Trends, LSTM

1. INTRODUCTION

Early research on the cryptocurrency market found evidence of speculative behaviour [11], yet the literature remains divided on whether this is the primary driver of price action. More recent research has focused on non-speculative price drivers. It has been shown that fundamental factors such as transaction volume and the number of tokens in existence [7], mining cost [1] and the number of active users [8] may predict cryptocurrency prices over the long term. Short-term price moves appear to be more closely related to internet search volumes and investor sentiment. Kristoufek [6] was one of the first to conclude that daily Wikipedia[3] traffic and weekly Google search volumes are correlated to the Bitcoin price. A recent study [9] continued this research and found a positive relationship between internet search volumes, Wikipedia activity and price, which becomes more pronounced during price bubbles.

Investor sentiment extracted from news articles [4] and Twitter[4] [3] appears to be positively correlated to the Bitcoin market. More focused social media activity has been shown to have predictive power in the Bitcoin market, with internet forum posts carrying more weight than tweets [10]. Similar predictive qualities were detected when analysing user activity in online cryptocurrency communities [5, 10]. The rise of Telegram as the de facto messaging platform for the cryptocurrency community has created a data source that combines the volume of Twitter with the focus of community forums. As far as we are aware, no studies using Telegram as a data source have yet been published.

Earlier studies on sentiment and internet search volumes relied largely on low frequency daily and weekly data, and in many cases used linear econometric models. Such architectures may fail to capture the granularity and complexity of the relationships that may exist between cryptocurrencies and their price drivers.

This paper evaluates the predictive power of Google Trends and Telegram with respect to Bitcoin and Ethereum price movements. It addresses shortcomings in earlier research by making use of higher frequency data and non-linear machine learning models.

2. DATA

A SQL-based infrastructure was designed to collect and store data on Bitcoin, Ethereum and their respective price drivers over a period of seven months from 1 December 2017 to 30 June 2018, encompassing 5,088 hours. Hourly data on price and trading volume was collected from a market data aggregator. The relative hourly popularity of the search terms 'bitcoin' and 'ethereum' (not case sensitive) was obtained from Google Trends. User messages from the largest and most active public Telegram chat groups dedicated to Bitcoin and Ethereum trading, respectively, were collected. This amounted to roughly one million messages.

[1]https://trends.google.com/trends. Accessed 1 September 2018.
[2]https://telegram.org. Accessed 1 September 2018.
[3]https://en.wikipedia.org. Accessed 1 September 2018.
[4]https://twitter.com. Accessed 1 September 2018.

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3. SENTIMENT ANALYSIS

Sentiment was extracted from the Telegram data using VADER [2], an open source text-based sentiment analysis library for Python. The sentiment scores assigned by VADER typically range from -1.0 (most negative) to 1.0 (most positive), but VADER's default dictionary failed to assign appropriate sentiment scores to discussions relating specifically to cryptocurrency trading. To address this, the dictionary was expanded with financial terminology as well as the most common words in the cryptocurrency social dialect. The latter included acronyms such as FUD for "fear, uncertainty, doubt" and slang words such as "lambo", which refers to a highly profitable trade, and "moon", used as a verb to indicate that the price of a cryptocurrency is expected to rise substantially. The sentiment scores assigned to sample phrases before and after updating the dictionary are shown in Table 1, illustrating a clear improvement when the domain specific lexicon is added.

Table 1: Sentiment analysis calibration.

Phrase	Sent. before	Sent. after
Sample cryptocurrency phrases		
This token will moon	0.0	0.71
We will all lambo!	0.0	0.74
I expect more fud	-0.33	-0.58
Sample financial phrases		
Buy the dip	0.0	0.54
I expect a rally	0.0	0.61
BTC will go exponential again	0.0	0.61
This is a bear market	0.0	-0.54
I expect a correction	0.0	-0.61
The market will crash soon	0.0	-0.71

Hourly average sentiment was calculated and stored in the database. In addition to sentiment scores, the number of messages per hour was calculated for each group. This indicator provides a broad, objective measure of the level of activity within a given cryptocurrency community, supplementing the more granular, subjective sentiment analysis performed by VADER.

Further preprocessing steps included removing outliers, irrelevant observations and seasonality. Stationarity was achieved by calculating the logarithmic hourly change in the value of each non-stationary time series. The data was smoothed over periods of up to one week to iron out some of the short-term noise inherent in high frequency observations. A sliding window approach was used, moving the smoothing window forward by one hour for each observation.

4. CORRELATION ANALYSIS

The preprocessed data was analysed to obtain a better understanding of each time series prior to using it as an input in the predictive model. The Bitcoin dataset was analysed first. Trading volume was found to be negatively correlated to price, indicating that rallies are characterised by an absence of sellers rather than an abundance of buyers, while downward moves are amplified by more sellers entering the market. The correlation between price and volume becomes more negative during periods of volatility, such as from 26 January to 15 February 2018, when the Bitcoin price declined from roughly \$11,000 to \$6,000, before recovering to nearly \$10,000. The Pearson correlation during this three-week period was -0.82 with a p-value of <0.001. This temporary increase in negative correlation may be a result of forced selling or panic-driven behaviour.

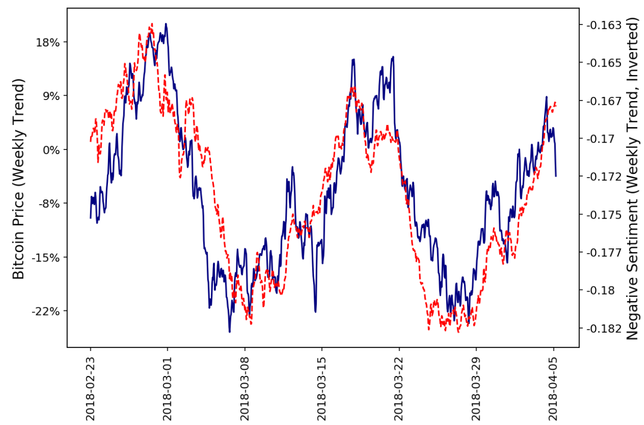

Figure 1: Negative sentiment (dashed red, right axis) plotted against the Bitcoin price (solid navy, left axis) for the six weeks from 23 February to 5 April 2018.

Bitcoin-related internet search queries historically exhibited a positive correlation to price. The correlation during the first two weeks of December 2017 was indeed strongly positive, but turned strongly negative by June 2018. This inversion of the relationship calls into question the persistence of the positive correlations uncovered in earlier research. It also highlights one of the key weaknesses of internet search volumes as a tool for price prediction: it is a crude measure of sentiment, highlighting only whether a topic is popular among internet users, but not whether it is so for positive or for negative reasons.

The four Telegram time series - positive, negative and composite sentiment, as well as the number of messages per hour - all exhibited behaviour that is correlated in some way to the Bitcoin price. Composite sentiment displayed a positive relationship to the Bitcoin price, with the relationship varying in strength from month to month. Positive sentiment displayed a weaker positive correlation to price than combined sentiment. Furthermore, it also appeared to lag, rather than lead, price movements. This may be indicative of celebratory behaviour, with group participants using positive language in response to positive market movements. Negative sentiment exhibited a weak but statistically significant negative correlation to price over the seven-month period. This statistic hides a more interesting dynamic, whereby strong negative relationships appear for periods lasting several weeks. An example of such a period is provided in Figure 1. It is not clear why these correlations change over time, although the correlation appears to be more negative when the market is rising or falling sharply. Unlike positive and composite sentiment, the negative sentiment variable appears to move largely in lockstep with the Bitcoin price and at times a few hours ahead of it.

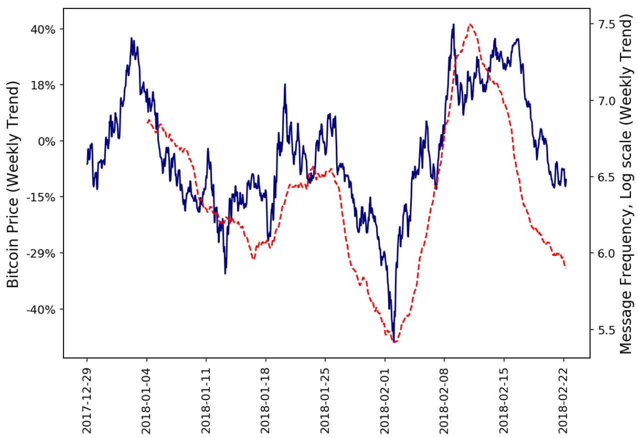

Figure 2: The number of messages per hour posted in the Bitcoin Telegram group, lagged by one week (dashed red, right axis) plotted against the Bitcoin price (solid navy, left axis) for the eight weeks from 29 December 2017 to 22 February 2018.

The number of Telegram messages posted per hour exhibited a near-zero correlation to price over the full seven-month period. However, when lagged by one week, a visible relationship emerged and the correlation increased to 0.36. At certain times the correlation rose further, such as during the first eight weeks of 2018, when it reached 0.79 with a p-value of <0.001 (see Figure 2). The strength of this relationship is unexpected. It may indicate that the activity in the Bitcoin Telegram group is an accurate proxy for the broader Bitcoin community's investment behaviour in the week that follows. Alternatively, the members of this Telegram group may have sufficient clout in the cryptocurrency market to influence the Bitcoin price over the short term.

The Ethereum dataset was analysed using a similar approach. As with Bitcoin, the relationship between internet search volumes and the Ethereum price inverted during 2018. However, the relationship between sentiment and price was weaker and less stable, possibly due to the smaller size and lower message frequency in the Ethereum Telegram group compared to the Bitcoin Telegram group.

5. MODEL AND METHODOLOGY

A suite of LSTM models was developed to evaluate the predictive power of each data source. The models predicted cryptocurrency price movements over periods ranging from one hour to one week, using price, trading volumes, internet search volumes, Telegram sentiment and Telegram message frequency as inputs. The models used binary classification to predict whether the price of a cryptocurrency would rise (class 1) or fall (class 0) during the period under consideration.

To maintain the path-dependent nature of the observations, the historic data was split into chronologically ordered subsets, with observations from December 2017 to April 2018 used for training, May 2018 for validation and June 2018 for testing. This reduced leakage by ensuring that no validation data would be seen during the training phase, and no test data would be seen during the training and validation phases. All testing on the validation and test sets was thus representative of what the models would encounter when used for real-time price prediction: out-of-sample observations from market conditions that differ from those that the models were trained and tested on.

6. EMPIRICAL RESULTS

Binary classification was performed using four model configurations for each of the two cryptocurrencies. The baseline model uses price and trading volumes as the only inputs. The Google Trends model builds upon the baseline model by adding internet search traffic as an additional input. Similarly, the Telegram model expands the baseline model by adding sentiment and message frequency data. Finally, a combined model was tested, combining all the aforementioned inputs. A summary of the most accurate binary classification models is presented in Table 2. The most accurate model for each cryptocurrency is presented in bold.

Table 2: Performance metrics of the four model configurations for Bitcoin (BTC) and Ethereum (ETH).

Currency	Pred. period	Train acc.	Valid. acc.	Test acc.	Test prec.	Test F1
Baseline Model						
BTC	1 Week	0.73	0.59	0.62	0.31	0.38
ETH	5 Days	0.67	0.76	0.64	0.65	0.64
Expanded Model: Google Trends						
BTC	1 Week	0.75	0.58	0.64	0.66	0.50
ETH	**1 Week**	**0.74**	**0.78**	**0.85**	**0.83**	**0.83**
Expanded Model: Telegram						
BTC	**1 Week**	**0.88**	**0.56**	**0.76**	**0.74**	**0.74**
ETH	4 Days	0.82	0.64	0.63	0.63	0.63
Combined Model						
BTC	4 Days	0.94	0.76	0.63	0.63	0.63
ETH	1 Week	0.68	0.54	0.56	0.52	0.47

For Bitcoin, the baseline model appeared to have some predictive power, with the best accuracy achieved over a one-week prediction period. However, the precision of this model was low. Accuracy improved only marginally when using Google Trends as an additional input. This was expected, given the inversion of the relationship between internet search volumes and the Bitcoin price during the first half of 2018. Using Telegram data enhanced the model noticeably, reaching 76% accuracy on the test set when predicting price direction over a one-week period. Switching from the Telegram model to the combined model led to a deterioration in performance: the benefit of extra information provided by the additional inputs appears to be offset by the increased complexity of the combined model.

The results imply that the Bitcoin Telegram group generates information that have predictive power. This may be due to several factors. The Telegram group in question has a predefined topic, which creates a structured discourse. This is rarely found in other social platforms such as Twitter, where numerous filters such as hashtags, user selection and keyword detection must be employed to hone in on a desired topic. The fact that Telegram as a data source is under-researched at present means it is more likely to contain valuable trading signals. However, its predictive power may decline as more market participants use this data source for their trading algorithms. Investor sentiment extracted from Telegram may be more appropriate for price prediction than that obtained from Google Trends, as active members of trading discussion groups on Telegram are more likely to be active participants in the cryptocurrency market than Google users who simply search for the words "bitcoin" or "ethereum".

For Ethereum, the baseline model delivered better-than-random accuracy over periods up to one week. In contrast to Bitcoin, Ethereum prices were predicted most accurately by Google Trends data. This model achieved 83% accuracy on the test set. Telegram data generated predictions that were broadly similar to that of the baseline model, indicating that this data source has limited predictive power in the Ethereum market. This may be ascribed to the Ethereum Telegram group's smaller size and lower message frequency, being less than a quarter of that of the Bitcoin Telegram group.

It is surprising that the Google Trends model produced very different results for Bitcoin and Ethereum, as the correlation between internet search volumes and both of these cryptocurrencies inverted during the period under review. It is possible that the predictive power of Google Trends in the Ethereum market has not yet been eroded by increased competition as it has in the Bitcoin market, given Ethereum's smaller investment community. Alternatively, the strong performance of the Google Trends model on the Ethereum test set may be spurious; this hypothesis can be evaluated by conducting additional testing over different time periods.

7. CONCLUSION

The experimental results support the hypothesis that Google Trends and Telegram data can predict the direction of short-term cryptocurrency price movements. Telegram was shown to be the better predictor of Bitcoin price movements and Google Trends was shown to be the better predictor of Ethereum price movements. The best results for both cryptocurrencies were achieved when making predictions over a one-week period.

Of further interest is the finding that, in contrast to earlier studies, the correlation between internet search volume and the price movements of Bitcoin and Ethereum turned strongly negative during 2018. Positive correlations were detected between sentiment and price, and the frequency of messages posted in the Bitcoin Telegram group was shown to lead price movements by one week.

The predictive models developed during this research may find applications in the investment industry. A caveat applies: complex financial models can have severe unintended negative consequences if poorly understood. As such, the neural networks presented in this paper should be implemented only by those practitioners with sufficient understanding of the model's underlying mechanics.

Future research may apply this paper's experimental framework to other financial instruments and time periods to determine whether the findings apply more generally and whether the relationships persist over time. Furthermore, a formal investigation into causality may shed light on the direction of causality between the various time series under investigation.

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