SCHOOL OF
ELECTRICAL AND
ELECTRONIC ENGINEERING

THE UNIVERSITY of ADELAIDE

Modelling the Dynamics of Cryptocurrency Market

Jeremy Abbot
(Partner: Nikolaos Flabouris)

ELEC ENG 4068 Honours Project

Date submitted: 1st June 2018
Supervisors: Derek Abbott, Azhar Iqbal, Matthew Sorell

Acknowledgments

I would like to thank my partner Nikalous Flabouris for working on this project, and our supervisors Derek Abbott, Azhar Iqbal and Matthew Sorrell for guiding us and offering suggestions to expand our project.

Abstract

In order to discover the effects of trading between cryptocurrencies has on the prices of the cryptocurrency market, an agent-based model that simulates the market has been produced. At current, the model contains two traders and a single cryptocurrency. Information on how search trends affect or are affected by the cryptocurrency price has been researched to prepare for the next stage of the model.

Contents

1 Introduction

1.1 Motivation

There has been a large interest in the cryptocurrency market, especially recently as Bitcoin's price has reached several thousand dollars. The success of Bitcoin has prompted many other cryptocurrencies being formed in a similar vein - some successful, and others failing. But how do these developing cryptocurrencies affect the price of other cryptocurrencies on the market? And is there some way of predicting how the market will change?

1.2 Objectives

This project will attempt to model the workings of the cryptocurrency market, and compare the effect that cryptocurrencies have on one another when traded.

2 Previous Studies

There has been other studies surrounding the cryptocurrency market, with a large portion focused on Bitcoin.

Luisanna Cocco Et al (2015) Uses agent-based modelling with two agent types to simulate trading fiat currency with bitcoin. As this is a similar topic to what is planned, this will be the building block to the model that shall be developed.

Adam S Hayes (2016) looks at identifying the likely determinants of crytpocurrency value, examining 66 such currencies, and develops a cost-of-production model involving current exchange rates, the relative cost to mine for coins, and competition to produce said coins. This focuses heavily on the production of cryptocurrency from the perspective of the miners, and may possibly be useful for how the agents in the developed model may think.

Abber ElBahrawy Et al (2017) identifies the stable factors in the cryptocurrency market, such as the number of active cryptocurrencies, distribution of shares, and the birth and death rate of new currencies. Many of these factors will be implemented in the upcoming model, especially the stated factors above.

Ross C Phillips and Denise Gorse (2017) uses Markov models to detect the start of a cryptocurrency price bubble through social media usage. Similarly, Young Bin Kim Et al (2016) analyses user comments on online cryptocurrency communities to predict price changes. To investigate another possible factor, the correlation between Google search trends and the change in cryptocurrency price will be researched prior to the construction of the model.

3 Background

Blockchain is the main building block for most cryptocurrencies. It is a online, decentralised, public ledger, where transactions are recorded, in blocks, and cannot be removed once inserted. Each cryptocurrency uses a different blockchain to record the transactions.

Blocks in the blockchain are inputed through the use of a peer-to-peer consensus algorithm. The peers in the algorithm - called "miners" - record each transaction that has taken place for the given currency, and periodically compare and order all transactions such that all miners' records are identical. This information is then recorded as a block and attached to the end of the blockchain (Melanie Swan, 2015).

4 Project Management

4.1 Project Deliverables

There are a few deliverables in the project, as shown in Table 1. The milestones, in bold, have a hard deadline, and as such must be completed by the specified date. All other deliverables (such as the market simulations) have flexible deadlines, and are what is planned to be completed, with the expectation that they adhere to the deadlines set.

Deliverable	**Deadline**
Market simulation v1.0	30th April
Thesis Draft	1st June
Market simulation v2.0	August
Market simulation v3.0	Semptember
Project Wiki x2	22nd October
Youtube video	22nd October
Exhibition	22nd October
Thesis	26th October
Final Seminar	30th October

Table 1: Project Deliverables

4.2 Division of Labour

At current, labour has been divided between the first version of the market simulation and gathering the data that is required for the subsequent version of the simulation. Further allotment of tasks will be delegated once both portions of the current work has been completed.

4.3 Knowledge Gaps and Challenges

As the project is very heavily submerged in the realm of economics, there are a variety of theoretical knowledge from that feild that will be required in order to effectively model a market. Other knowledge that will be required will include the numerical values of currency birth and death rates, number of active traders, the average fiat currency spent on transactions and the standard deviation.

The challenges that may be faced are largely programming-related, such as developing a viable model, and ensuring the program works as expected.

4.4 Requirements and Constraints

The topic itself requires multiple cryptocurrencies to be simulated, with a variety of traders involved in the transactions for the model. It requires the use of real world data such that it may predict the results of the future market.

5 Method

In order to develop an effective model of the market, a number of successive models that build upon one another must be completed. The first model will be an agent-based model in the same strain as Luisanna Cocco Et al (2015). This involves modelling a market that contains a single cryptocurrency that traders can buy and sell with a single fiat currency. The model also contains two types of agents: random traders, which randomly buy and sell pseudorandomly; and calculated traders, or chartists, who buy and sell when there is a steady increase or decrease of the market respectively. The model also included a random injection of cryptocurrency coins to simulate the mining process. The model will be designed in C++, as prior knowledge with the language has been most prominent.

To improve the effectiveness of the model, various factors will be tested and compared against the real-world cryptocurrency market to see what effect it has. The factors that will be compared are Google search data - which will be found using Google trends - and Tor traffic - found on Tor metrics. The following models will incorporate the findings.

The second model will expand upon the previous model, incorporating another cryptocurrency that traders can trade using both fiat currency and the original cryptocurrency. Other types of trader types will also be added, including traders that only buy a certain cryptocurrency, and others that trade with the cheaper or expensive currency.

Expanding on the model once again, the introduction of more cryptocurrencies will be added to the model at different timesteps. This will simulate new currencies being introduced to the market, which can then be analysed to see if new currencies has an effect on the currently existing market.

6 Progress Report

Thus far, there has been work towards verifying whether media presence regarding cryptocurrency has an effect on the price of the cryptocurrency itself. To gauge this presence, Google trends has been used, comparing the search terms Bitcoin, Ripple, and Ethereum with the price of the respective cryptocurrency. The data has been measured since the beginning of Bitcoin, with one sample a week due to the constraints imposed by Google Trends. This may lead to possibly inaccurate results.

The cross correlation was found using a code run on Matlab as found in Appendix A. The correlation tested was for cryptocurrency price versus the search trends on Google and against other cryptocurrencies, as shown in Figures 1 and 2 respectively.

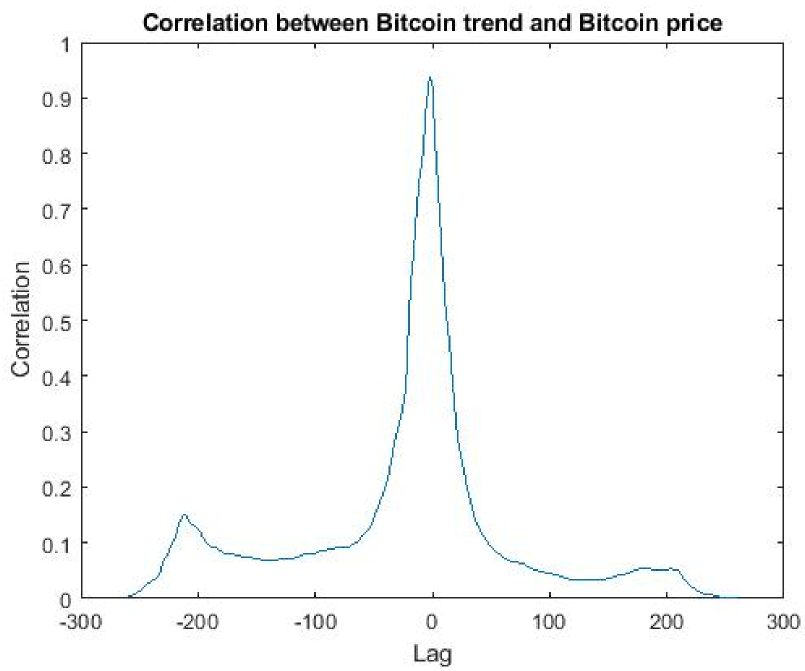

Figure 1: The cross correlation between the Bitcoin trend on Google and the Bitcoin price

To find the points where correlation is significant, the absolute value of those points must be greater than $\frac{2}{\sqrt{n-|k|}}$, where n is the number of samples, and k is the lag of the largest

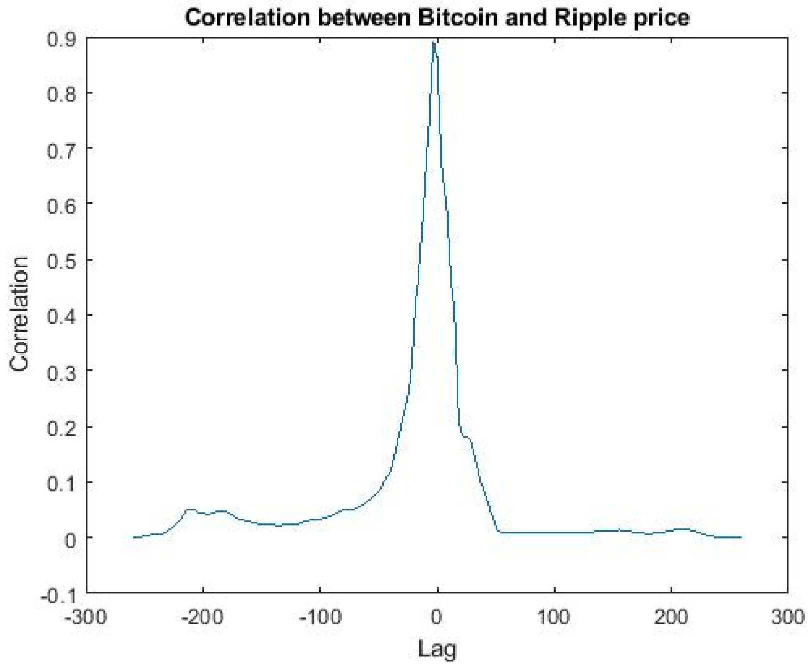

Figure 2: The cross correlation between the Bitcoin price and the Ripple price

peak or trough. Using 261 samples from the data, and the lag values found in Table 2, it was found that the significance values were generally at 0.124.

Data 1	**Data 2**	**Lag at Maximum Value**	**Significance Value**
Bitcoin Trend	Bitcoin Price	-2	0.124
Ripple Trend	Ripple Price	-2	0.124
Ethereum Trend	Ethereum Price	-5	0.125
Bitcoin Price	Ripple Price	-1	0.124
Bitcoin Price	Ethereum Price	-3	0.125
Ripple Price	Ethereum Price	-1	0.124

Table 2: Cross correlation lags and their significance values

As such, it is generally found that most significant values are between -50 and 20 lag. One exception to this was Ripple, (see Figure 3) where the significant values occurred starting from -250. This may be due to interference from searches using other definitions of the word 'ripple'.

The prominently negative significant values combined with the fact that most maximum lag values are negative lead to the assumption that the Google search trends lead the cryptocurrency price, and as such has an effect on the market price change. As these samples are in measurements of weeks, the Google search results seem to lead by approximately 2 weeks. Similarly, Bitcoin price seems to lead Ripple's price by one week and Ethereum by 3 weeks.

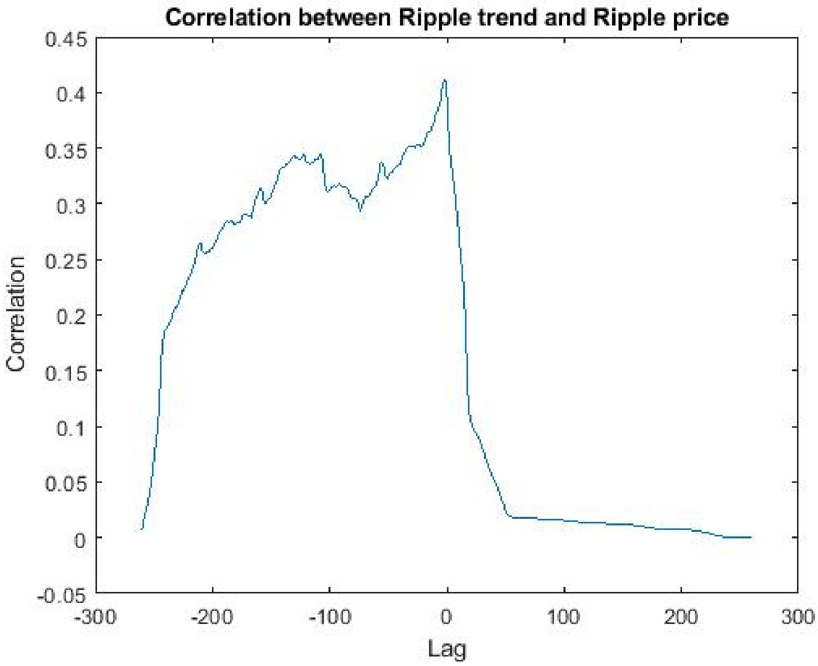

Figure 3: The cross correlation between the Ripple trend on Google and the Ripple price

Tor data was gathered from Tor metrics with samples every day. As with the Google trends data, the cross correlation between the Tor bandwidth used each day was compared to the price of the cryptocurrency. The resulting graphs (similar to what is shown in Figure 4) indicated a lag of 0 for all cryptocurrencies.

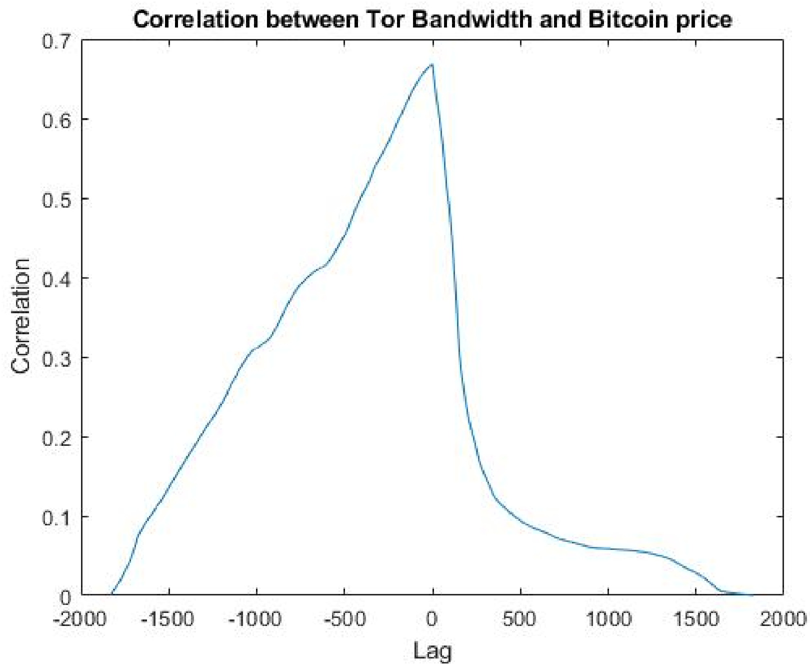

Figure 4: The cross correlation between the Tor bandwidth used and the price of Bitcoin

7 Conclusions

Beginning by comparing Google search trends to the value of cryptocurrency on the market, it was found that there is a correlation between the Google search trends for cryptocurrency and the prices of the respective cryptocurrency. Similarly, there is also a correlation between the change in prices between each cryptocurrency. In both cases, more thorough research (such as daily samples) may be required to test this.

7.1 Future Work

With the current findings, the next logical step would be to incorporate the Google trend data into the model that has been developed. The metrics for Tor usage will be researched in a similar fashion. The model will also require more types of traders and cryptocurrencies to simulate and compare the effects that the new currency has on the previous market.

A Appendix: Source Code

Cross correlation code

```
M = readtable(”CryptoNumbers.csv”, ’Format’, ’%{dd/mm/yy}D%f%f%f%f%f%f%f%f%f%f%f%f%f’);

Fs = 7;

[r,lag] = xcorr(M.BTCTrend,M.BTC,’coeff’);

[~,I] = max(abs(r));

lagDiff = lag(I)

timeDiff = lagDiff/Fs

figure

plot(lag,r)

title(’Correlation between Bitcoin trend and Bitcoin price’);

xlabel(’Lag’);

ylabel(’Correlation’);
```

References

[1] Luisianna Cocco, Giulio Concas, Michele Marchesi, "Using an Artificial Financial Market for Studying a Cryptocurrency Market," *Journal of Economic Interaction and Coordination,* 2017, vol. 12, pp. 345-365.

[2] Adam S Hayes, "Cryptocurrency value formation: An empirical study leading to a cost of production model for valuing bitcoin," *Telematics and Informatics,* 2017, vol. 34, pp. 1308-1321.

[3] Abeer ElBahrawy, Laura Alessandretti, Anne Kandler, Romualdo Pastor-Satorras and Andrea Baronchelli, "Evolutionary dynamics of the cryptocurrency market," *Royal Society Open Science,* [online] 2017, 4:170623, Viewed 28th February 2018, http://dx.doi.org/10.1098/rsos.170623.

[4] Ross C Phillips and Denise Gorse, "Predicting Cryptocurrency Price Bubbles Using Social Media Data and Epidemic Modelling," *IEEE Symposium Series on Computational Intelligence,* 2017, vol. 6 no. 1.

[5] Young Bin Kim, Jun Gi Kim, Wook Kim, Jae Ho Im, Tae Hyeong Kim, Shin Jin Kang, Chang Hun Kim, "Predicting Fluctuations in Cryptocurrency Transactions Based on User Comments and Replies," *PLoS ONE* 2016, vol. 11 no. 8.

[6] Melanie Swan, *Blockchain*, 1st ed., O'Reilly Media Inc., 2015.

[7] Google Trends, "Google Trends," May 2018, `https://www.google.com/trends`

[8] The Tor Project, "Tor Metrics," May 2018, `https://metrics.torproject.org`

Glossary and Symbols

Fiat currency: A physical currency that is legal tender in a given country.