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. Information on how search trends affect or are affected by the cryptocurrency price has been researched as a possible extension to the model. Results have been analysed to find the best performing traders and what factors lead to their growth.

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. It will also identify if factors such as Google search trends and Tor activity has an impact on cryptocurrency prices.

2 Background

Blockchain is the fundamental building block for most cryptocurrencies. It is a permanent public ledger, where new transactions are appended to, as blocks. Each cryptocurrency uses a different blockchain to record the transactions.

The blockchain is decentralised, meaning there is no single location where it is stored, instead having a multitude of copies existing throughout the network. To ensure that the copies are correct, any new blocks to be appended are first verified through a consensus algorithm, where miners will make a majority decision on the contents of the block[1].

Mining is an important part of the cryptocurrency process. On top of verifying new blocks, miners collect the transactions that have occurred to add to the new blocks, and clearing a new space on the blockchain for the new block. This is done through the use of cryptographic hashing, where the data from the previous block is hashed with the new transactions and a nonce to reach a specified number as verified on the blockchain. Clearing space for a new block on the blockchain rewards the miners with a few coins of the cryptocurrency, as well as a fraction of the fees associated with the transactions on the new block [2].

3 Previous Studies

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

L. Cocco Et al (2015) Uses agent-based modelling to simulate trading fiat currency with Bitcoin. Incorporating two agent types, random traders and calculated traders, each trader is initially provided with a finite amount of fiat currency and Bitcoin, and uses that with their trading strategy to place orders. The mining process is not directly simulated, but Bitcoin is injected into some traders periodically to keep the increase of Bitcoin at a rate proportionate with that of reality. The resultant model reproduces some of the real-world properties, such as the scale of price fluctuations, the fat tail phenomenon found in most currency markets, and the volatility clustering of prices[3]. Using this model as a building block, the model can be extended to provide for a variety of cryptocurrencies..

A.S. Hayes (2016) looks at identifying the likely determinants of cryptocurrency value, examining 66 such currencies. Using a regression model, it finds that the three main drivers of cryptocurrency value occur due to the level of competition in the producer network, the unit production rate, and the algorithm difficulty for mining cryptocurrency. The conclusion states that the overall cost of production drives the price, and reducing the cost of production will inherently decrease the cost of cryptocurrency[4]. This focuses heavily on the production of cryptocurrency, and leads towards possible decision-making processes that mining traders in the model may take.

A. ElBahrawy Et al (2017) analyses the whole history of the cryptocurrency market and the behaviour of 1469 cryptocurrencies to identify a variety of factors in the market. It finds that, while the market capitalisation is increasing exponentially and a multitude of currencies are being added and removed, a variety of factors remain constant, such as the number of active cryptocurrencies, distribution of shares in the market, and the birth and death rate of new currencies[5]. Using the results from this research, the model can utilise the constants found to make assumptions on factors such as distribution of currency and active currencies.

R.C. Phillips Et al (2017) uses a hidden Markov model to detect the start of a cryptocurrency price bubble through social media usage. Validating the use of such model, it then builds a trading strategy and tests it against historical data, where it outperforms the general buy and hold strategy. This indicates the value of social media in regards to cryptocurrency prices[6].

Similarly, Y.B. Kim Et al (2016) analyses user comments on online cryptocurrency communities to predict price changes. Focusing on Bitcoin, Ethereum and Ripple, they crawled through the online cryptocurrency communities for the number of topics, number of replies, dates, and the url associated with the forum, and rates each post from very negative to very positive. The causality between the range of response types with the fluctuation of the associated cryptocurrency price was tested and found that comments on the forums did affect the price of its respective cryptocurrency[7]. Due to the influence of these studies, it was decided to investigate into other possible factors such as Google search trends and Tor activity.

4 Method

In order to develop an effective model of the market, a number of external factors were tested to see what impacts the change in cryptocurrency prices. In this case, the Google search trends from Google Trends[8] and Tor usage from Tor Metrics[9] were compared against Bitcoin, Ethereum, and Ripple to determine if they needed inputting into the model. These factors were decided on as a high portion of the population use Google to navigate the internet, an important requisite in purchasing cryptocurrency. Tor was investigated as an external factor due to the high associativity between Bitcoin and criminal activity on the deep net, of which Tor is the most commonly used browser that can access it[10].

The model itself was constructed through a number of successive models that build upon one another. It was initialised as an agent-based model in the same strain as L. Cocco Et al (2015)[3]. This involved modelling a market that contains a single cryptocurrency that traders can buy and sell with 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 was designed in C++, as prior knowledge with the language has been most prominent.

The second stage of the model expanded upon the previous model, incorporating multiple cryptocurrencies that traders can trade using both fiat currency and the original cryptocurrency. The value of each currency was initialised based on data from Coin Metrics[11], providing prices that range from the birth of the currency to the current day.

The model was analysed to determine the most effective trading strategy using 1000 traders, of which 700 were random, to simulate a general market, and 300 calculated traders, who made decisions based on the price change of cryptocurrencies over a one week period. The initial wealth of the traders was developed as a random value based on the distribution of Bitcoin from BitInfoCharts[12], adjusted for price, as very little information on coin distribution is available for other cryptocurrencies. To simulate the mining process in the market, a randomised 3% of traders gained periodic amounts of a cryptocurrency.

The analysis of the model will assume that the fiat currency is constant due to the difference in volatility between fiat currencies and cryptocurrencies as shown in Figure 1, and will be expressed in terms of US$ to be consistent with the sourced data [11].

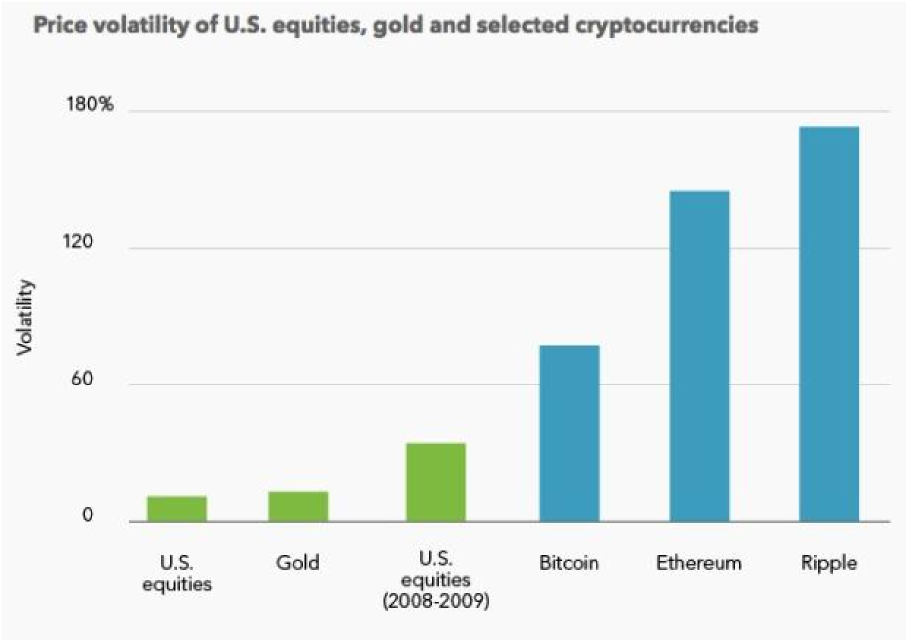

Figure 1: The price volatility of US equities and cryptocurrency [13]

5 Results

5.1 Google Trends and Tor Correlation

To gauge the media presence effect on cryptocurrency, 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 2 and 3 respectively.

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 peak or trough. Using 261 samples from the data, and the lag values found in Table 1, it was found that the significance values were generally at 0.124.

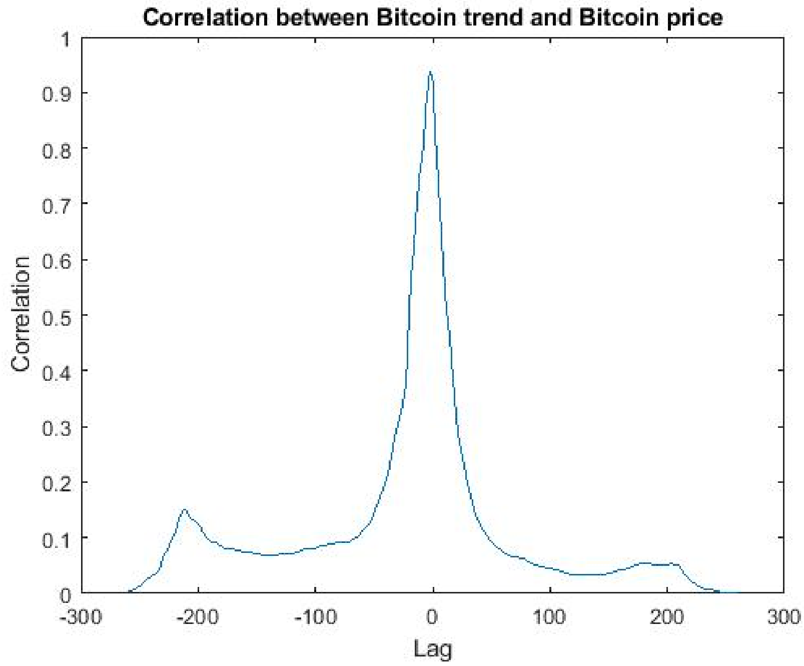

Figure 2: The cross correlation between the Bitcoin trend on Google and the Bitcoin price

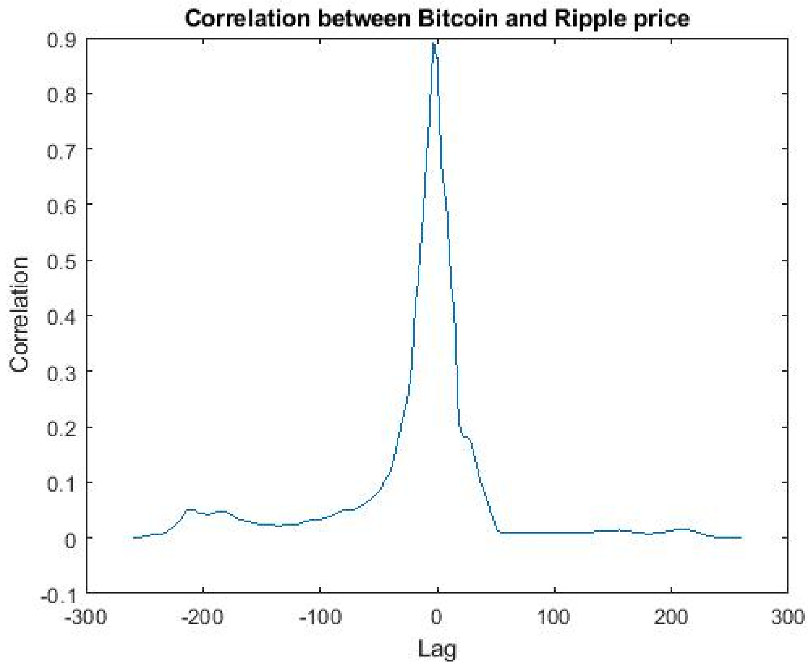

Figure 3: The cross correlation between the Bitcoin price and the Ripple price

As such, it is generally found that most significant values are between -50 and 20 lag. One exception to this was Ripple, (see Figure 4) 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

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 1: Cross correlation lags and their significance values

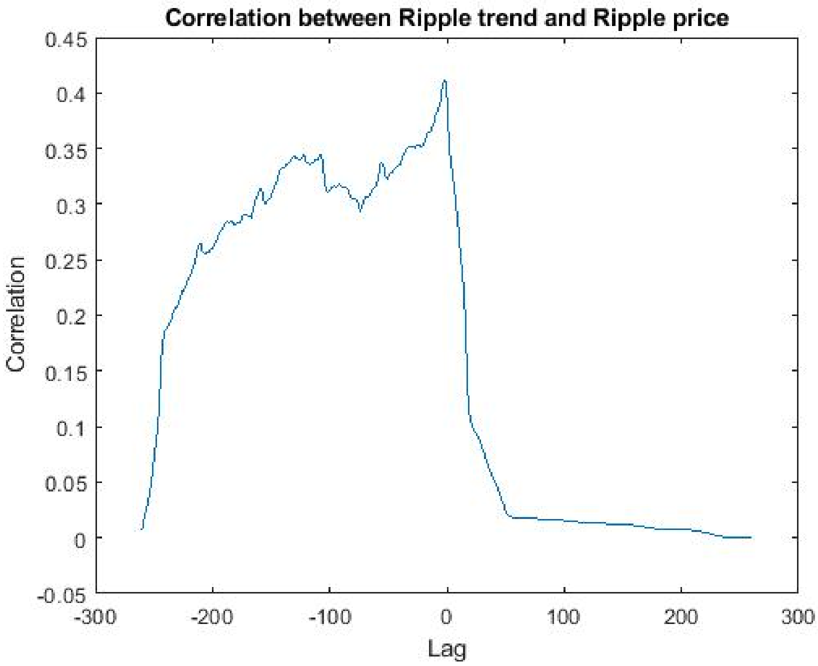

Figure 4: The cross correlation between the Ripple trend on Google and the Ripple price

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.

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 5) indicated a lag of 0 for all cryptocurrencies.

Overall, the data is correlated and tends to lead towards a causal relationship between Google search terms, Tor activity and cryptocurrency prices, however due to time restraints and difficulties in causal mathematics, insufficient evidence is provided to prove that there is a causal relation between Google trends and cryptocurrency prices, and similarly with Tor

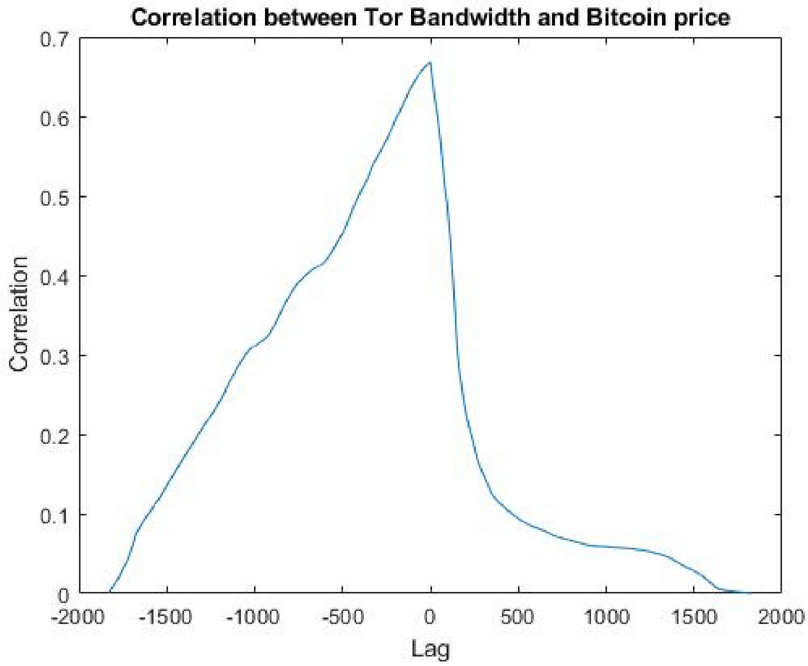

Figure 5: The cross correlation between the Tor bandwidth used and the price of Bitcoin

data. As such these factors have not been implemented in the model.

5.2 Model Results

Over the course of twenty runs, data was gathered on both the effectiveness of the traders and the fluctuation of cryptocurrency prices.

When comparing the performance of the currencies, both Ethereum and Ripple seemed to perform most effectively, with Ripple slightly outdoing Ethereum. However, most tests involved all the currencies decreasing in price significantly, and the positive performances occurred by a slight margin. The results can be seen in Table 2.

Currency	**Number of Best Performances**	**Number of Positive Performances**	**Average Daily Change(%)**
Bitcoin	3	2	-0.42
Ethereum	8	1	-0.34
Ripple	9	6	-0.20

Table 2: Performance of the model's cryptocurrencies

The price fluctuations seemed to be approximately normal centered around the average daily change as stated in Table 2, displayed in Figure 6.

By net wealth, more traders ended up running at a loss, with very few traders making a

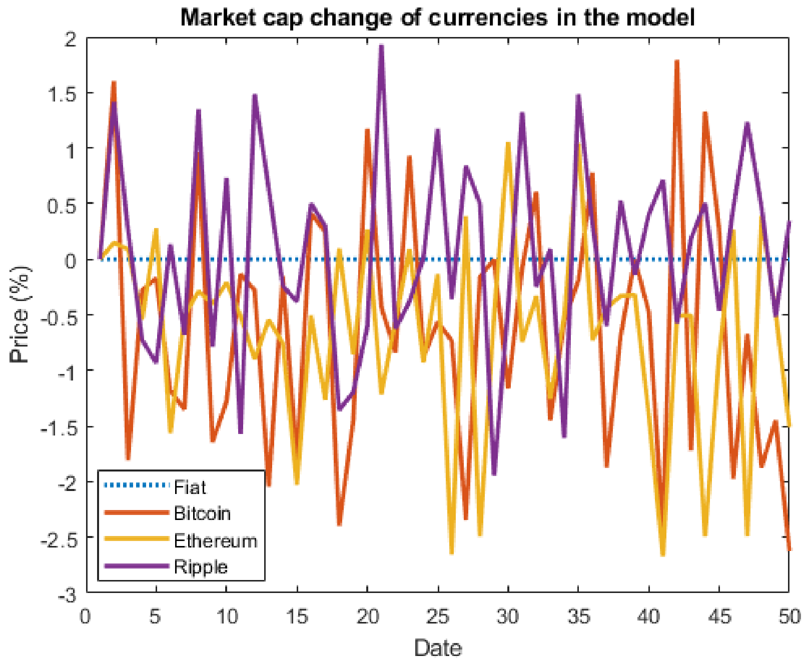

Figure 6: The price fluctuation of each cryptocurrency

profit (as shown in Figure 7). Of the 1000 traders in the model, the average calculated trader ranked 505th, while the average random trader ranked 499th.

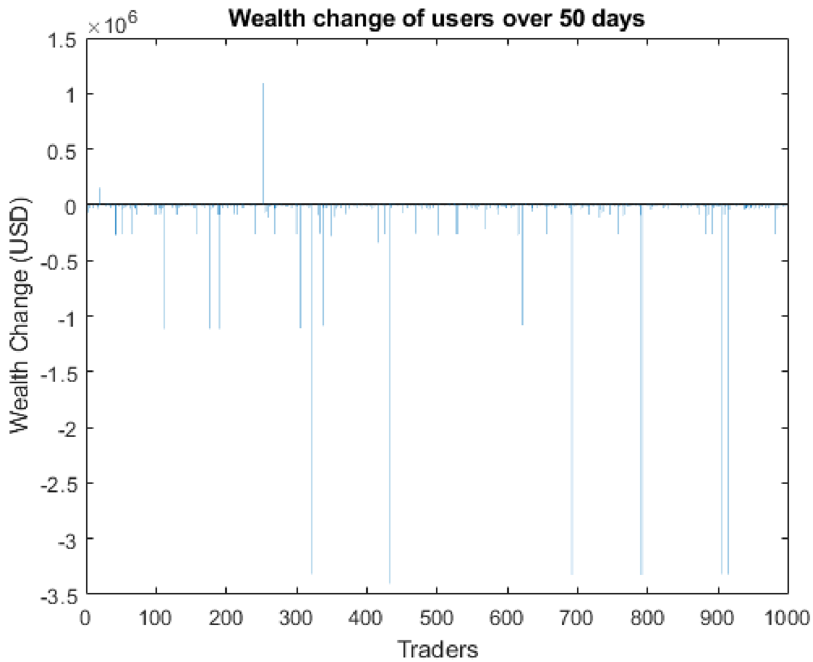

Figure 7: The performance of all traders by the net wealth gained

When comparing the percentage gain of the traders, while the same number lost/gained wealth, the overall bias was skewed towards the positive axis, (Figure 8). In this case the average calculated trader performed better, ranking at 480th, and the average random trader performing at 508th.

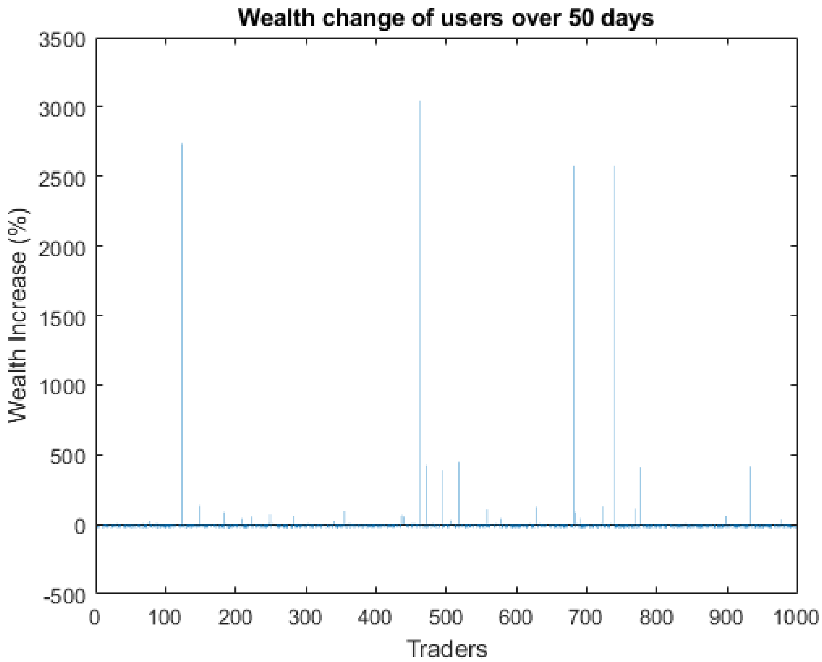

Figure 8: The performance of all traders by the percentage of wealth gained

6 Discussion

Due to the larger range of the initial wealth distribution than the currency price changes, it can be assumed that the growth percentage is a more precise metric to measure the effectiveness of traders. As such, it can be stated that the calculated traders performed better than the random traders. Upon looking into the best performing traders, it was found that they were all miners of currencies, providing excess currency from their initial pool (shown in Figure 9). The effect of the mining process may indicate that miners are being awarded too much wealth for their contributions.

Comparing the currency performance with trader performance showed that there was a trader for each currency that performed the best by net value in the cases where said currency has had a positive performance. Looking into this further, it was found that these traders started with a high initial value of currency. This may indicate that the assumption made for the wealth distribution of the cryptocurrencies was incorrect.

Comparing the currency results with that of reality shows that the model is under-performing when it comes to the prices of cryptocurrencies. This can be seen in Figure 10, with similar trends occurring even in cases where a currency performed positively. This may indicate that traders were less likely to buy, possibly due to the calculated traders selling currencies

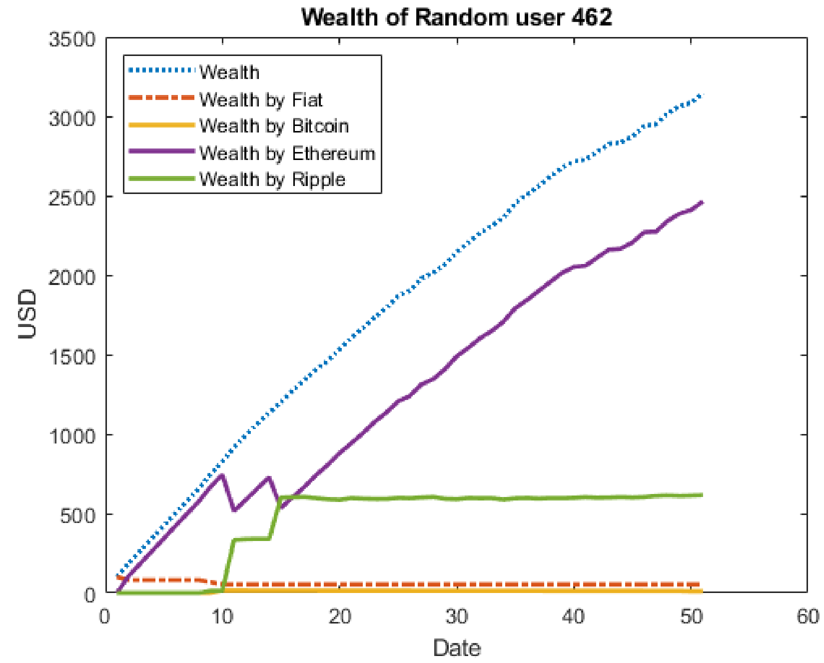

Figure 9: The best performing trader in one of the runs, being a miner of Ethereum

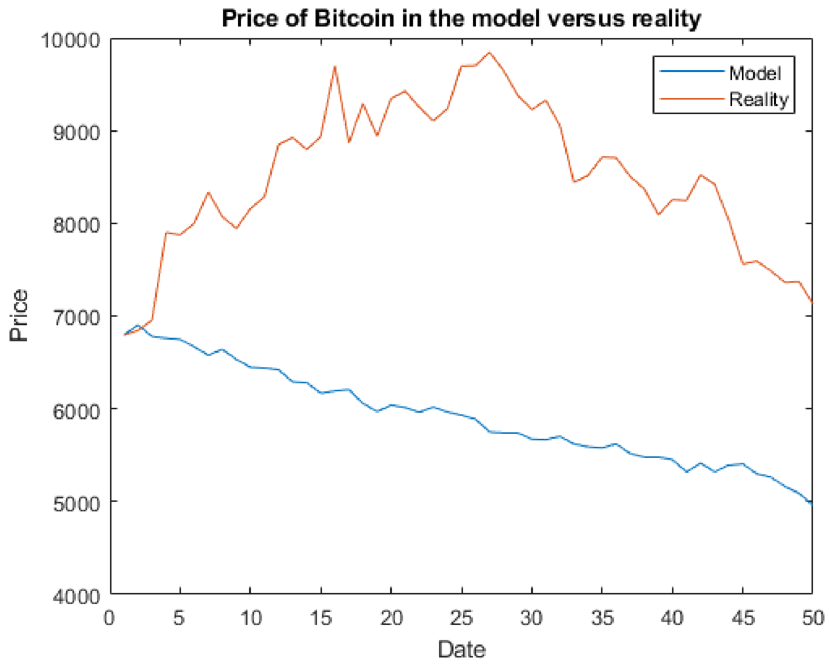

Figure 10: A comparison between Bitcoin prices in the model versus reality

that reduce in wealth, leading to a negative spiral in the model. Using this, it can be stated that the cryptocurrency market should not be able to work as effectively as it does in reality. This leads to the conclusion that cryptocurrencies may only be effective due to external influences, such as criminal activity, political issues, and other current affairs.

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. However, insufficient evidence is provided to prove if there is a causal relationship. A model was developed where the calculated traders performed well and the most profitable strategy is to become a miner, though due to a variety of factors they may not perform well in reality. This leads to external current affairs as a possible lead into the longevity of the cryptocurrency market.

7.1 Future Work

A baseline model has been produced, and can be further experimented upon to develop other possible calculated algorithms for traders, using methods such as stochastic calculus. The presence of mining will need to be reduced, and distribution of wealth could be refined. Defining a causal relationship between cryptocurrencies and Google search terms and Tor could be identified to further enhance the model, and other external factors - such as political decisions - could be measured to improve the results. Further extension could include more currencies, and adding random births and deaths of cryptocurrencies.

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’);

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’);
```

B Appendix: Project Management

B.1 Project Deliverables

There are a few deliverables in the project, as shown in Table 3. 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 3: Project Deliverables

B.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.

B.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.

B.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.

References

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

[2] S. Nakamoto, *Bitcoin: A Peer-to-Peer Electronic Cash system* Oct. 2008

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

[4] A.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.

[5] A. ElBahrawy, L. Alessandretti, A. Kandler, R.P. Satorras, A. 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.

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

[7] Y.B. Kim, J.G. Kim, W. Kim, J.H. Im, T.H. Kim, S.J. Kang, C.H. Kim, "Predicting Fluctuations in Cryptocurrency Transactions Based on User Comments and Replies," *PLoS ONE* 2016, vol. 11 no. 8.

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

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

[10] WhoIsHostingThis?, "The Deep Web, The Dark Web & Tor : The Definitive Guide," October 2018 `https://www.whoishostingthis.com/blog/2017/03/07/tor-deep-web/`

[11] Coin Metrics, "Coin Metrics" October 2018, `https://coinmetrics.io/data-downloads/`

[12] BitInfoCharts, "BitInfoCharts," October 2018, `https://bitinfocharts.com/top-100-richest-bitcoin-addresses.html`

[13] J. Detrixhe, "Ripples XRP crypto token is more volatile than just about everything" February 2018, `https://qz.com/1216880/ripples-xrp-crypto-is-more-volatile-than-ethereum-bitcoin-stocks-and-gold/`

Glossary and Symbols

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