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Herding behavior in the cryptocurrency market

Abstract

This study investigates the relationship between herding behavior and the cryptocurrency market. The exploded interest in cryptocurrencies and still growing attention for behavioral finance made research like this necessary. Several standards tests from finance have been used to examine this relationship. Input for those tests mainly consists daily prices and daily returns of a selected group of cryptocurrencies during a specified time period. Results of those tests contradict each other, which means no one-sided conclusion can be drawn with respect to the relationship between herding behavior and the cryptocurrency market.

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1. Introduction

Currencies functioning without a central bank or institution. While not too long ago this was considered impossible, in the present paying with and trading in cryptocurrencies is a widespread phenomenon. Failure of governments and central banks made room for an alternative payment method (Weber, 2014). Interest in the cryptocurrency market kept growing over time and so did investments in the market, resulting in a total market capitalization of $384.791.000.000 at 17/05/2018 (www.CoinMarketCap.com). In other words, cryptocurrencies have taken over the charts and its implications are more relevant than ever. To quote Lloyd Blankfein, CEO of Goldman Sachs: "It's arrogant to think cryptocurrency won't be successful" (Young, 2018).

The cryptocurrency hype grew strong over the past years, with its peak around the turn of 2017. Bitcoin, at the moment the most expensive cryptocurrency, reached a height of no less than $19.345,49 (www.finance.yahoo.com). Trading in cryptocurrencies finds its existence in the Blockchain technology, in which interest is still growing rapidly as well. Everybody appeared to get into the cryptocurrency trade, even when their knowledge was not even slightly sufficient to make rational decisions.

1.1 Financial theories

Traditional finance theory is to a great extent about investors making rational decisions on a rational market. Investors would do so by collecting all information available about different outcomes. This information is use to make an investment decision that would maximize utility to the greatest extent, keeping in mind the risk aversion of investors.

Over the years it became clear that this rationality assumption does not always apply in practice. So a shift in interest became clear, behavioral finance was getting more attention over time. Behavioral finance seeks its explanations in combining psychological theory with traditional finance.

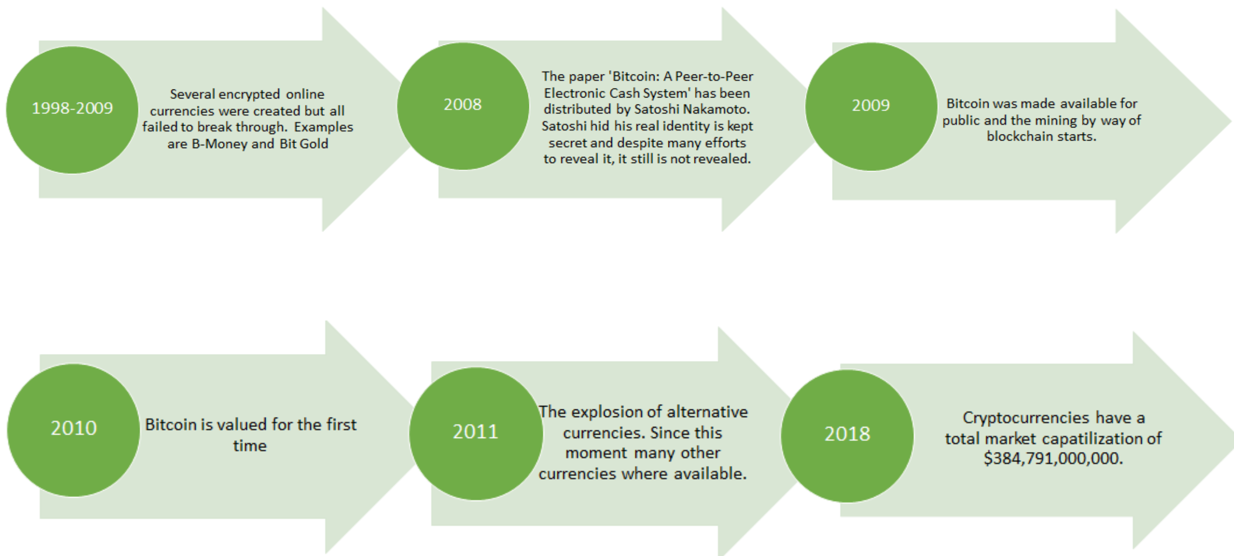
Behavioral finance theorists believe that individuals actually try to make rational decisions, but are often simply not capable of doing so, because of both their capacities and recourses. After initial resistance for behavioral theories by traditional finance theorists, it soon became clear behavioral finance could explain for many anomalies of the traditional finance theory (Baker & Greg, 2013).

One of the subjects within behavioral finance concerns herding behavior. Herding behavior explains the phenomena of individuals mimicking actions of larger groups, while probably not making the same decisions by themselves. Mimicking can be the consequence of different causes, like lack of available information or the infamous fear of missing out. Consequences of herding behavior contain miss-pricing, extreme volatilities and sometimes even market crashes (Hwang & Salmon, 2004).

1.2 Cryptocurrencies

Cryptocurrency is short for cryptographic currency. The reason why cryptocurrencies are seen as such innovating is because it is the first actual decentralized currency. Instead of a transaction via a bank or another third party, the transaction immediately goes to the receiver. Part of its strength is its resistance to fraud. Blockchain, the working force behind cryptocurrencies, can be seen as a huge digital ledger where all transactions are saved. However, its uniqueness lies in the fact that there is no actual central database where all transactions are stored. This database gets copied and updated every moment by its users, creating millions of databases all containing the same information, making the system resistant to fraud (Nakamoto, 2008). Figure 1 shows a brief history of the development of cryptocurrencies over the years.

Figure 1: Brief timeline of cryptocurrencies



The rapid growth of the market capitalization is financed by millions of sources from all over the world, while the currency does not even contain a real underlying value. Despite Blockchain being one of the most innovative developments of the last decades, my belief is that a big part of the enormous investments in cryptocurrencies is a consequence of herding behavior, and that is what will be examined during the paper using several standard finance tests.

Research question: Does herding behavior effect expresses itself in cryptocurrency?

The research question will be investigated throughout the paper in the following way. Section 2 elaborates the data and methodology. Section 3 contains comprehensive results of the research. Section 4 concludes.

2. Data and Methodology

2.1 Methodology

To examine the relationship between herding behavior and cryptocurrencies a combination of different standard tests from finance research will be used. First an Augmented Dickey Fuller test will be carried out to test whether the prices of cryptocurrencies follow a random walk. In other words, stationarity will be examined to investigate whether cryptocurrency markets are efficient to some degree. Following up correlations will be calculated and finally the lead-lag relationship between the currencies will be investigated. The last will be done by performing a Granger causality test and a paired t-test to explore whether the price of cryptocurrencies could be predicted. Finally, the relationship between returns on currencies and the investor sentiment index of Baker and Wurgler will be look upon.

2.2 Data

The sample set of cryptocurrencies will contain the daily prices of the 5 cryptocurrencies with the biggest market capitalization at 17/05/2018. This concerns the following currencies: Bitcoin, Ethereum, Ripple, EOS and Litecoin. Table 1 summarizes the most important characteristics. All this data was available at and exported from www.coingecko.com

Considering the resemblance in the price charts of the majority of cryptocurrencies it is assumed that this sample is representative for cryptocurrencies in general.

Table 1: Characteristics of the cryptocurrencies

Symbol	***Name***	***Price***	***Market Cap***
BTC-USD	Bitcoin	$8308.42	$141.556
ETH-USD	Ethereum	$699.60	$69.603
XRP-USD	Ripple	$0.6898	$26.423
EOS-USD	EOS	$13.20	$8.621
LTC-USD	Litecoin	$132.69	$7.504

Source: Yahoo Finance   *Where Market Cap is defined in billions of dollars.*

Important to note is that Bitcoin Cash originally was part of the top 5 as well, but putting both Bitcoin and Bitcoin Cash in the sample would bias the research too much. Graph 1 shows the enormous similarity between the two currencies over time.

Graph 1: Bitcoin vs. Bitcoin Cash

Source: Yahoo Finance

2.3 Time period

Trading in cryptocurrencies is a relatively young concept, at the time of writing EOS has not even existed for a year. The existence Bitcoin, Ethereum, Ripple and Litecoin concerns a more extensive time period, but prices just started fluctuating less than 18 months ago. For EOS, the earliest possible historical prices available date from 7/19/2017.

Despite the fact the other four currencies contain a more extensive history of prices, it is decided to use historical prices starting from 7/19/2017 as well. Working with time periods of different lengths would make the currencies harder to compare and in that case the quality of the research would be affected. The last observation date taken into consideration for each currency is 5/13/2018, at the time of writing the most recent possible date. Graph 2 compares the price trends of the five currencies during the time period tested for in this research.

Summarized the dataset will contain the daily historical prices of Bitcoin, Ethereum, Ripple, EOS and Litecoin in the period 7/19/2017 until 5/13/2018.

Important to keep in mind is the different between the prices of regular stocks and cryptocurrencies. While the market for regular stocks is just opened 5 days per week during daytime, the market for cryptocurrencies is never closed. Prices of regular stocks are therefore only updated during opening hours of the market, while the prices of cryptocurrencies are updated every second.

Graph 2: Comparison of the five currencies

Source: Yahoo Finance

3. Results

3.1 Random walk

To examine whether the prices of the various cryptocurrencies follow a random walk, use has been made of the Augmented Dickey Fuller (ADF) test. The three different processes that have been examined under the null hypothesis of non-stationarity are the following:

1. Random walk without drift (*regular)*
2. Random walk with drift (*drift)*
3. Random walk with or without drift (*trend)*

Important to keep in mind is the fact that Dickey Fuller tests work the other way around compared to regular tests in finance research. If a null hypothesis cannot be rejected, one could conclude that this variable contains a unit root and the stationarity assumption needs to be rejected. In this particular case this implies that when the null hypothesis cannot be rejected, the price of the currency tested follows a random walk.

The critical value will be set on the regular level of 5%, what leads to the critical values displayed in table 2.

Table 2: Critical values of different processes

Process	Critical Value
Regular	-2.878
Drift	-1.650
Trend	-3.428

The Augmented Dickey fuller tests have been carried out on the data set and time period discussed in section 2, which led to 308 observations. Table 3 shows the results of the different Dickey Fuller tests, the comprehensive results of each currency can be found in the appendix A.

Table 3: T-values of currencies

Currency	Regular	Drift	Trend
BTC	-1.651	-1.651	-1.425
ETH	-1.445	-1.445	-1.558
XRP	-1.698	-1.698	-1.790
EOS	-1.063	-1.063	-2.375
LTC	-1.630	-1.630	-1.734

When table 1 and table 2 are juxtaposed, several important results become clear. When using the regular and the trend adjusted ADF test, the null hypothesis is rejected and all currencies suffer from non-stationarity.

However, when testing for a random walk with drift, stationarity depends on the currency. When testing for a random walk with drift, Bitcoin, Ethereum and Litecoin actually satisfy the stationarity assumption. It can therefore be stated that in this case for this currencies a random walk is not present. On the other hand, a random walk is still present for Ethereum and EOS.

Therefore it can be stated that when testing for a random walk without drift and a random walk with or without drift the market is efficient, at least to some degree. When testing for a random walk with drift this depends on the currency.

3.2 Correlations

A prominent way to compare different variables is to look at the correlations among the daily returns between the variables. However, the data set of this research contains daily prices instead of daily returns. Some modifications had to be made, daily returns are calculated by log differencing each currency. For example, dBTC implies daily returns of Bitcoin

Table 4 summarizes the correlations among the daily returns of the five cryptocurrencies and shows the p-values of each correlation variable in brackets.

Table 4: Correlations of daily returns among currencies

	dBTC	**dETH**	**dXRP**	**dEOS**	**dLTC**
dBTC	1.0000				
dETH	0.6313 (0.000)	1.0000			
dXRP	0.4000 (0.000)	0.5818 (0.000)	1.0000		
dEOS	0.0684 (0.2316)	0.0735 (0.1980)	0.1059 (0.0635)	1.0000	
dLTC	0.6103 (0.000)	0.7257 (0.000)	0.4676 (0.000)	-0.0645 (0.2590)	1.0000

The correlations among Bitcoin, Ethereum, Ripple and Litecoin are all between 0.4000 and 0.7257. Furthermore, all correlation coefficients are significant at a confidence level of 95%. On the other hand, EOS shows low correlations with every other currency examined, and moreover, each of its correlations is insignificant.

These results, aside from EOS, implies the presence of a relationship among daily returns of cryptocurrencies

The next step is to analyze correlations between the daily returns of cryptocurrencies and the stock market. The log differences of the daily prices of the Dow Jones Industrial Average (DOW) will represent the daily prices of the stock market between 7/19/2017 and 5/13/2018. As earlier mentioned, a big difference exists between the market for cryptocurrencies and the regular stock market, the regular stock market is closed 2 days per week.

To compare them either way, the dataset needed some extra modifications. Within the dataset of cryptocurrencies, all Saturdays and Sundays removed, which ensured an equal period of time. Table 5 summarizes the correlations between daily returns on cryptocurrencies and the stock market and shows the p-values of each correlation variable in brackets.

Table 5: Correlations between daily returns of currencies and the stock market

	BTC	**ETH**	**XRP**	**EOS**	**LTC**	**DOW**
BTC	1.0000					
ETH	0.5841 (0.000)	1.0000				
XRP	0.3889 (0.000)	0.5384 (0.000)	1.0000			
EOS	0.1146 (0.0961)	0.0711 (0.3030)	0.1145 (0.0964)	1.0000		
LTC	0.5605 (0.000)	0.6744 (0.000)	0.4317 (0.000)	-0.0404 (0.5589)	1.0000	
DOW	0.0855 (0.2149)	0.1412 (0.040)	0.0792 (0.2509)	0.0517 (0.4538)	0.1265 (0.0660)	1.0000

Despite modifications in the data set of cryptocurrencies, correlations of daily returns among the currencies hardly change. Correlations among Bitcoin, Ethereum and Litecoin are comparable to the correlations in table 4 and the correlation coefficients are still significant, while EOS still shows uncorrelated daily returns.

The correlation between daily returns on the stock market and cryptocurrencies is low and mainly insignificant. This implies that daily returns of the stock market and daily returns on cryptocurrencies are hardly related.

3.3 Granger causality tests

To asses a lead-lag relationship between the sample set of currencies, Granger causality tests have been employed. Within the Granger causality test it is important to choose the optimal number of lags, resulting in a model that best fits the data.

To determine what amount of lags should be used, the optimal number of lags will be examined based on three information criteria: the Akaike Information Criterion (AIC), the Schwarz Bayesian Information Criterion (SBIC) and the Hannan-Quinn Information Criterion (HQIC). The time period will contain daily returns of Bitcoin, Ethereum, Ripple, EOS and Litecoin from 7/19/2017 until 5/13/2018, what will imply a total of 298 observations. The daily returns are calculated by log differencing each currency.

A pre-estimation of the lag-order selection statistics for a Vector Auto Regression (VAR), with a maximum of 10 lags has been made and produced the results shown in table 6.

Table 6: Pre-estimation of lag-order selection statistics for a VAR for a maximum of 10 lags

Lag	LL	df	p	FPE	AIC	HQIC	SBIC
0	2008.01	25		1.0 e-12	-13.4430	-13.4182	-13.3810
1	2089.47	25	0.000	6.8 e-13*	-13.8219*	-13.6729*	-13.4497*
2	2106.91	25	0.090	7.2 e-13	-13.7712	-13.4980	-13.0888
3	2124.75	25	0.076	7.6 e-13	-13.7232	-13.3259	-12.7306
4	2141.5	25	0.119	8.0 e-13	-13.6678	-13.1463	-12.3651
5	2163.27	25	0.012	8.2 e-13	-13.6461	-13.0005	-12.0333
6	2180.1	25	0.115	8.6 e-13	-13.5913	-12.8215	-11.6683
7	2206.78	25	0.001	8.6 e-13	-13.6025	-12.7086	-11.3694
8	2223.94	25	0.101	9.1 e-13	-13.5500	-12.5319	-11.0067
9	2244.42	25	0.023	9.4 e-13	-13.5196	-12.3774	-11.6661
10	2273.9	25	0.000	9.1 e-13	-13.5497	-12.2833	-10.3860

For the information criteria, a lower absolute score yields an estimation closer to the truth. The AIC, HQIC and SBIC are all in favor of a lag number of 1 with scores of respectively -13.8219, -13.6729 and -13.4497. The logical consequence of observations is to estimate a VAR model with 1 lag.

Subsequently a Vector Auto Regression with the proper amount of lags will be carried out, the time period and sample set used will be the same. The extensive results of the Vector Auto Regression can be found in appendix B.

Now the proper models and data are generated, the lead-lag relationship between the different currencies can be assessed. As mentioned before, this will be employed by a Granger causality test. More specifically, use will be made of a Wald test of a VAR model with 1 lag. The results are shown in table 7.

Table 7: Granger causality Wald Test 1 lag

Equation	Excluded	chi2	Df	Prob > chi2
dBTC	dETH	1.3332	1	0.248
	dXRP	0.7654	1	0.382
	dEOS	3.3015	1	0.069
	dLTC	1.1169	1	0.291
	ALL	12.7950	4	0.012
dETH	dBTC	0.01876	1	0.891
	dXRP	3.0282	1	0.082
	dEOS	1.2991	1	0.254
	dLTC	1.1581	1	0.282
	ALL	4.5930	4	0.332
dXRP	dBTC	1.9204	1	0.116
	dETH	0.1670	1	0.683
	dEOS	2.3336	1	0.127
	dLTC	1.7296	1	0.188
	ALL	4.5488	4	0.337
dEOS	dBTC	9.1627	1	0.002
	dETH	2.3910	1	0.122
	dXRP	8.0762	1	0.004
	dLTC	3.2951	1	0.069
	ALL	112.62	4	0.000
d**LTC**	dBTC	1.6507	1	0.199
	dETH	3.4991	1	0.061
	dXRP	0.8322	1	0.362
	dEOS	0.0071	1	0.933
	ALL	6.7008	4	0.153

A quick reminder: A Granger causality Wald test reveals causality only if the lags of the independent variables predict the dependent variable, while the dependent variable does not predict the independent variable. Under the null hypothesis the lagged independent variables do not cause the dependent variable and the alternative is they actually do cause the independent variable. Granger causality will be discussed separately for each currency.

3.3.1 Bitcoin

The null hypothesis that the coefficients on the two lags of Ethereum, Ripple, EOS and Litecoin themselves are jointly zero cannot be rejected. In other words, the null hypothesis that Ethereum, Ripple, EOS Litecoin Granger cause Bitcoin cannot be rejected as well.

On the contrary, the null hypothesis that the coefficients of the four currencies are jointly zero actually gets rejected. That means Ethereum, Ripple, EOS and Litecoin jointly do not Granger cause Bitcoin.

3.3.2 Ethereum

Granger causality takes the same role in the case of Ethereum. Bitcoin, Ripple, EOS and Litecoin do Granger cause Ethereum. Different from the case of Bitcoin, the null hypothesis that the coefficients of the four currencies are jointly zero cannot be rejected, implicating the four currencies do Granger cause Ethereum.

3.3.3 Ripple

The case of Ripple does not differ from the results of the Granger causality test on Ethereum. Just like the four currencies separately do not Granger cause Ripple, they Granger cause Ripple jointly as well.

3.3.4 EOS

The results of EOS are an exception compared to the results of the other Granger causality Wald tests. Bitcoin and Ripple do not actually Granger cause EOS, while Ethereum and Litecoin do. On the contrary, the null hypothesis that the coefficients of the four currencies are jointly zero gets rejected as well. This means the four currencies do not Granger cause EOS jointly.

3.3.5 Litecoin

The results of the Granger causality Wald test of Litecoin are the same as of Ethereum and Ripple. Both the four currencies do Granger cause Litecoin separately like they do jointly.

Again, the purpose of the Granger causality tests is to see if a variable, in this case a currency, can predict the returns of the other currency. If so, an investor could make easy profits by observing one currency now to forecast the future returns of another currency.

In general can be stated, with some exceptions, that in most cases Granger causality is existing. In other words, in general can be stated that it should be possible to forecast the movement of a currency by exploring another currency.

3.4 Paired t test

To avoid confusion, a paired t-test has been carried out in addition to the Granger causality Wald test. The t-tests have been performed on daily returns of every currency relative to every other currency. The time period is the same as in previous calculations and daily returns are again calculated by log differencing the prices of each currency. The extensive results can be found in appendix C. The null hypothesis of a t-test states that the mean difference of the variables is zero, implicating that the mean returns of different coins are not different from each other. Working with a confidence level of 95% implies the null hypothesis will be rejected if the calculated p-values are smaller than 0.05. Table 8 displays the absolute differences in average returns and the p-values generated by the different t-tests below those returns in brackets.

Table 8: Paired t-test

	BTC	ETH	XRP	EOS	LTC
BTC	-				
ETH	0.0005277 (0.8606)	-			
XRP	0.0003984 (0.9363)	0.0001293 (0.9762)	-		
EOS	0.0022022 (0.7355)	0.0027298 (0.6230)	0.0026005 (0.7272)	-	
LTC	0.0005109 (0.8837)	0.0000168 (0.9956)	0.00011250 (0.9821)	0.0027130 (0.7176)	-

As can be seen in table 8, not one p-value comes even close to the 0.05 boundary. This implies a mean difference in daily returns of zero between all currencies.

3.5 Investor sentiment index

The investor sentiment index of Malcolm Baker and Jeffrey Wurgler is one of the major developments in finance in the last few years. Baker and Wurgler demonstrated a significant influence of investor sentiment on cross sectional stock prices. Results of the paper showed evidence of systematic risk not being thorough as explanation for returns, at which investor sentiment actually contributed to that particular explanation.

Baker and Wurgler have constructed a monthly index based for investor sentiment. The updated version of the index and more information can be found at Jeffrey Wurglers website (*http://people.stern.nyu.edu/jwurgler/*). On the basis of this index, a forecast can be made about the actual returns of stocks in that particular month. One of the most important implications of Baker and Wurgler for this paper disclosed a positive relationship between high sentiment and low returns for stocks attractive to optimists and speculators, where cryptocurrencies can be categorized under. At the same time, low sentiment yielded high returns for this kind of stocks. A higher sentiment index would imply extremer returns (Baker & Wurgler, 2006). What should be noted is that the research was done on regular stocks. Therefore the index is actually meant to implement on regular stocks and not necessarily on cryptocurrencies.

The last part of the empirical part of this paper contains an application of the investor sentiment index on cryptocurrencies. There will be taken a look into the relationship between cryptocurrencies and the investor sentiment index. What made implementing the index on the original sample set problematic, was the fact that the index is only updated and calculated up to and including September 2015, so even before the first observation date of the time period of the sample set.

The following solution has been devised. Bitcoin finds its existence years before the other currencies and already experienced noteworthy fluctuations in its price earlier than the time period used in this research. To be precise, this concerned the period between July 2013 and December 2014, as can be seen in graph 3. Therefore it was decided to look into the relationship between returns of Bitcoin in this particular period and the corresponding sentiment index values. Because of the previously revealed similarities between the returns of the different currencies within the sample set, the results of this particular part will be generalized for all the currencies within the sample set. The generalization unfortunately gives the need to mention concerns regarding potential caveats to the interpretation of the results

Graph 3: Bitcoin Price Chart between 2013 and 2015

Source: Yahoo Finance

Baker and Wurgler constructed a composite investor sentiment index that could forecast return as explained above. Thereafter they orthogonalized the index to create cleaner proxies for investor sentiment. In this paper use will be made of the orthogonalized sentiment index instead of the regular index, for that reason. The proxies for both indexes and the monthly returns on Bitcoin for the determined time period are shown in table 9.

Table 9: Investor sentiment index and monthly returns on Bitcoin

Month - Year	Sentiment index	Orthogonalized Sentiment Index	Monthly Return Bitcoin
07-2013	- 0.20	0.09	+ 0.41 %
08-2013	- 0.12	0.05	+ 32.22 %
09-2013	- 0.09	0.06	- 4.91 %
10-2013	- 0.14	- 0.01	+ 61.03 %
11-2013	- 0.19	- 0.07	+ 461.14 %
12-2013	- 0.08	0.05	- 34.58 %
01-2014	- 0.27	- 0.14	+ 9.93 %
02-2014	- 0.24	- 0.14	- 29.38 %
03-2014	- 0.23	- 0.12	- 20.00 %
04-2014	- 0.25	- 0.12	- 0.83 %
05-2014	- 0.20	- 0.09	+ 41.79 %
06-2014	- 0.16	- 0.04	+ 0.69 %
07-2014	- 0.02	0.05	- 9.53 %
08-2014	- 0 07	0.00	- 16.52 %
09-2014	- 0.01	0.05	- 19.91 %
10-2014	- 0.10	- 0.07	- 12.95 %
11-2014	- 0.04	- 0.02	- 11.79 %
12-2014	0.00	0.01	- 15.85 %

Source Sentiment Indexes: http://people.stern.nyu.edu/jwurgler/

Source Monthly Returns: https://www.investing.com/crypto/bitcoin/btc-usd-historical-data

As said before, a high sentiment would imply low returns for stocks attractive to optimists and speculators and vice versa. As for the results in table 9, no relationship seems to exist between the orthogonalized sentiment index and the monthly returns of Bitcoin. In other words, there is no proof the existence of investor sentiment on cryptocurrencies.

4. Conclusion

This paper examined the relationship between herding behavior and cryptocurrencies based on different standard finance tests. A brief overview of the results of the empirical tests will be presented to attach several conclusions and implications to these results.

Different random walk tests revealed different results. When testing for a random walk without drift and a random walk with or without drift, the market seems efficient at least to some degree. When testing for a random walk with drift this differs per currency. In general can be stated that this tests revealed that the cryptocurrency market seems quite efficient, at least to some degree.

Granger causality Wald tests pointed out that in the case of most currencies Granger causality is existing. In other words, in general can be stated that it is possible to forecast the movement of a currency by exploring another currency. This implies possibilities for investors to make easy profits by observing one currency now to forecast the future returns of another currency. Following up paired t-tests were performed, and the tests indicated a mean difference of zero in daily returns between all currencies.

When comparing daily returns among cryptocurrencies it became clear that, aside from EOS, a strong correlation exists among them. However, examining correlations between the different cryptocurrencies and the stock market showed other results. The correlation between daily returns on the stock market and cryptocurrencies is low and mainly insignificant. This implies that daily returns of the stock market and daily returns on cryptocurrencies are hardly related.

Looking into the relationship between Baker and Wurglers investor sentiment index did not indicate any significant relationships. However, the index is actually meant to implement on stocks, not on cryptocurrencies. The above discussed correlations between daily returns on the stock market and cryptocurrencies could explain for this. When the correlations of returns between the stock market and cryptocurrencies are small, indexes meant to make implications about regular stocks are not ideal to use on cryptocurrencies.

In conclusion, it can be stated that no one-sided answer to the research question can be given in this paper. While the markets seem quite efficient after non-stationarity tests, a Granger Wald test on the other side points out lead-lag relations between different currencies. Despite absence of investor sentiment according to the index of Baker and Wurgler, its cause can lie in the low correlations between returns on cryptocurrencies and returns on the regular stock market. All taken together, one could say that is unclear if herding behavior expresses itself in cryptocurrencies.

The results and conclusions give several ideas for further research. One limitation in this research is the sample set existing of 5 cryptocurrencies. One could carry out the same tests on a data set of daily returns and prices of much more currencies, to generate an extensive set of results. Another suggestion for further research concerns the investor sentiment index. As told before, the investor sentiment index is made to imply on regular stocks. One could modify the regression used in the calculations for the investor sentiment index, and make it more suitable for cryptocurrencies. When such research is performed, the index could explain more veracious for investor sentiment in cryptocurrencies.

5. Overview of literature

Baker, H. K., & Greg, F. (2013). Paradigm Shifts in Finance - Some Lessons from the Financial Crisis. *European Financial Review*.

Baker, M., & Wurgler, J. (2006). Investor Sentiment and the Cross-Section of Stock Returns. *The Journal of Finance 61(4)*, 1645-1680.

Hwang, S., & Salmon, M. (2004). Market stress and herding. *Journal of Empirical Finance 11*, 585-616.

Nakamoto, S. (2008). Bitcoin: A Peer-to-Peer Electronic Cash System. *www.bitcoin.org*, pp. 1-9.

Weber, B. (2014). Bitcoin and the legitimacy crisis of money. *Cambridge Journal of Economics 40(1)*, 17-41.

Young, J. (2018, June 21). Goldman Sachs CEO: It's 'Arrogant' to Think Cryptocurrency Won't be Succesful. *CNN*.

6. Appendix

6.1 Appendix A: Augmented Dickey Fuller tests for a Random walk

BTC	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value	p-value for Z(t)
Without drift	-1.651	-3.455	-2.878	-2.570	0.4563
With drift	-1.651	-2.339	-1.650	-1.284	0.0498
With or without drift	-1.425	-3.988	-3.428	-3.130	0.8533

ETH	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value	p-value for Z(t)
Without drift	-1.455	-3.455	-2.878	-2.570	0.5607
With drift	-1.445	-2.339	-4.650	-1.284	0.0748
With or without drift	-1.558	-3.988	-3.428	-3.130	0.8084

XRP	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value	p-value for Z(t)
Without drift	-1.698	-3.455	-2.878	-2.570	0.4323
With drift	-1.698	-2.339	-1.650	-1.284	0.453
With or without drift	-1.790	-3.988	-3.428	-3.130	0.7096

EOS	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value	p-value for Z(t)
Without drift	-1.063	-3.455	-2.878	-2.570	0.4676
With drift	-1.063	-2.339	-1.650	-1.284	0.0521
With or without drift	-2.375	-3.988	-3.428	-3.130	0.7096

LTC	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value	p-value for Z(t)
Without drift	-1.630	-3.455	-2.878	-2.570	0.4676
With drift	-1.630	-2.339	-1.650	-1.284	0.0521
With or without drift	-1.734	-3.988	-3.428	-3.130	0.7096

6.2 Appendix B: Vector Auto Regression (1 lag)

Sample	7/11/2017 – 5/13/2018	**Number of obs**	307
Log likelihood	2118.599	**AIC**	-13.60651
FPE	8.48e-13	**HQIC**	-13.46087
Det(Sigma_ml)	6.97e-13	**SBIC**	-13.24232

Equation	**Parms**	**RMSE**	**R-sq**	**chi 2**	**P>chi 2**
dBTC	6	.057121	0.0401	12.80903	0.0252
dETH	6	.063848	0.0149	4.632683	0.4623
dXRP	6	.092319	0.0173	5.394064	0.3697
dEOS	6	.087243	0.2685	112.6576	0.0000
dLTC	6	.075732	0.0215	6.74489	0.2403

		Coef.	**Std. Err.**	**Z**	**P>|z|**	**Confidence Interval**	
dBTC	dBTC L1.	.1474541	0.0753295	1.96	0.050	-.000189	.2950972
	dETH L1.	-.0973423	.0843062	-1.15	0.248	-.2625795	.0678949
	dXRP L1.	-.0378179	.0432353	-0.87	0.382	-.1225576	.0469218
	dEOS L1.	.058853	.0323902	1.82	0.069	-.0046306	.1223367
	dLTC L1.	-.696544	.0659074	-1.06	0.291	-.1988305	.0595216
	_cons	.0038828	.0032417	1.20	0.231	-.002707	.0102363
dETH	dBTC L1.	-.0115336	.0842017	-0.14	0.891	-.1765659	.1534987
	dETH L1.	-.007016	.0942357	-0.07	0.941	-.1917145	.1776826
	dXRP L1.	-.0840986	.0483275	-1.74	0.082	-.1788188	.0106217
	dEOS L1.	.0412654	.0362051	1.14	0.254	-.0296953	.1122261
	dLTC L1.	.0792789	.0736698	1.08	0.282	-.0651114	.2236691
	_cons	.0036594	.0036234	1.01	0.313	-.0034424	.0107613
dXRP	dBTC L1.	-.1687159	.121748	-1.39	0.166	-.4073376	.0699059
	dETH L1.	-.055682	.1362563	-0.41	0.683	-.3227394	.2113754
	dXRP	.0533163	.0698773	0.76	0.445	-.0836406	.1902732

	L1.						
	dEOS L1.	0.0799687	.0523493	1.53	0.127	-.022634	.1825714
	dLTC L1.	.1400883	.1065199	1.32	0.188	-.0686869	.3488635
	_cons	.0036507	.0052392	0.7	0.486	-.0066179	.0139193
dEOS	dBTC L1.	.348267	.1150536	3.03	0.002	.1227662	.5737679
	dETH L1.	.1991074	.1287641	1.55	0.122	-.0532655	.4514803
	dXRP L1.	.187663	.066035	2.84	0.004	.0582368	.3170891
	dEOS L1.	-.042565	.0494708	-0.86	0.390	-.1395259	.054396
	dLTC L1.	.1827267	.1006628	1.82	0.069	-.0145688	.3800221
	_cons	.0041549	.0049511	0.84	0.401	-.0055491	.0138588
dLTC	dBTC L1.	.1283158	.0998732	1.28	0.199	-.067432	.3240636
	dETH L1.	-.209084	.1117747	-1.88	0.061	-.4281584	.0099903
	dXRP L1.	-.0522911	.0573222	-0.91	0.362	-.1646405	.0600583
	dEOS L1.	.0036172	.042935	0.08	0.933	-.0805506	.0877849
	dLTC L1.	.086796	.0873811	0.99	0.321	-.0844679	.2580598
	_cons	.0037234	.0042978	0.87	0.386	-.0047002	.012147

6.3 Appendix C: Paired t test

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95 % Conf. Interval]	
dBTC	308	.003941	.0032967	.0578576	-.0025461	.014281
dETH	308	.0034133	.0036538	.0641237	-.0037763	.010603
Diff	308	.0005277	.0030017	.0526796	-.0053788	.0064342

mean(diff) = mean(dBTC - dETH)	t = 0.1758
Ho: mean(diff) = 0	degrees of freedom = 307

Ha: mean(diff) < 0	Ha: mean(diff) != 0	Ha: mean(diff) > 0
Pr(T < t) = 0.5697	Pr(|T| > |t|) = 0.8606	Pr(T > t) = 0.4303

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95 % Conf. Interval]	
dBTC	308	.003941	.0032967	.0578576	-.0025461	.014281
dXRP	308	.0035427	.0052728	.0925376	-.0068328	.0139181
Diff	308	.0003984	.0049764	.0873348	-.0093937	.0101904

mean(diff) = mean(dBTC - dXRP)	t = 0.800
Ho: mean(diff) = 0	degrees of freedom = 307

Ha: mean(diff) < 0	Ha: mean(diff) != 0	Ha: mean(diff) > 0
Pr(T < t) = 0.5319	Pr(|T| > |t|) = 0.9363	Pr(T > t) = 0.4681

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95 % Conf. Interval]	
dBTC	308	.003941	.0032967	.0578576	-.0025461	.014281
dEOS	308	.0061432	.0058466	.1026077	-.0053613	.0176477
Diff	308					

mean(diff) = mean(dBTC - dEOS)	t = -0.3381
Ho: mean(diff) = 0	degrees of freedom = 307

Ha: mean(diff) < 0	Ha: mean(diff) != 0	Ha: mean(diff) > 0
Pr(T < t) = 0.3677	Pr(|T| > |t|) = 0.7355	Pr(T > t) = 0.6323

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95 % Conf. Interval]	
dBTC	308	.003941	.0032967	.0578576	-.0025461	.014281
dLTC	308	.0034301	.004325	.0759035	-.0050803	.0119405
Diff	308	.0005109	.0034886	.0612249	-.0063538	.0073755

mean(diff) = mean(dBTC - dLTC)	t = 0.1464
Ho: mean(diff) = 0	degrees of freedom = 307

Ha: mean(diff) < 0	Ha: mean(diff) != 0	Ha: mean(diff) > 0
Pr(T < t) = 0.5582	Pr(|T| > |t|) = 0.8837	Pr(T > t) = 0.4418

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95 % Conf. Interval]	
dETH	308	.0034133	.0036538	.0641237	-.0037763	.010603
dXRP	308	.0035427	.0052728	.0925376	-.0068328	.0139181
Diff	308	-.0001293	.0043282	.07596	-.0086461	.0083874

mean(diff) = mean(dETH - dXRP)	t = -0.0299
Ho: mean(diff) = 0	degrees of freedom = 307

Ha: mean(diff) < 0	Ha: mean(diff) != 0	Ha: mean(diff) > 0
Pr(T < t) = 0.4881	Pr(|T| > |t|) = 0.9762	Pr(T > t) = 0.5119

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95 % Conf. Interval]	
dETH	308	.0034133	.0036538	.0641237	-.0037763	.010603
dEOS	308	.0061432	.0058466	.1026077	-.0053613	.0176477
Diff	308	-.0027298	.0066627	.1169292	-.0158401	.0103804

mean(diff) = mean(dETH - dEOS)	t = -0.4097
Ho: mean(diff) = 0	degrees of freedom = 307

Ha: mean(diff) < 0	Ha: mean(diff) != 0	Ha: mean(diff) > 0
Pr(T < t) = 0.3411	Pr(|T| > |t|) = 0.6823	Pr(T > t) = 0.6589

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95 % Conf. Interval]	
dETH	308	.0034133	.0036538	.0641237	-.0037763	.010603
dLTC	308	.0034301	.004325	.0759035	-.0050803	.0119405
Diff	308	-.0000168	.0030199	.059989	-.0059591	.0059255

mean(diff) = mean(dETH - dLTC)	t = -0.0056
Ho: mean(diff) = 0	degrees of freedom = 307

Ha: mean(diff) < 0	Ha: mean(diff) != 0	Ha: mean(diff) > 0
Pr(T < t) = 0.4978	Pr(|T| > |t|) = 0.9956	Pr(T > t) = 0.5022

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95 % Conf. Interval]	
dXRP	308	.0035427	.0052728	.0925376	-.0068328	.0139181
dEOS	308	.0061432	.0058466	.1026077	-.0053613	.0176477
Diff	308	-.0026005	.0074469	.1306932	.017254	.012053

mean(diff) = mean(dXRP - dEOS)	t = -0.3492
Ho: mean(diff) = 0	degrees of freedom = 307

Ha: mean(diff) < 0	Ha: mean(diff) != 0	Ha: mean(diff) > 0
Pr(T < t) = 0.3636	Pr(|T| > |t|) = 0.7272	Pr(T > t) = .6364

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95 % Conf. Interval]	
dXRP	308	.0035427	.0052728	.0925376	-.0068328	.0139181
dLTC	308	.0034301	.004325	.0759035	-.0050803	.0119405
Diff	308	.0001125	.0050181	.088068	-.0097618	.009968

mean(diff) = mean(dXRP - dLTC)	t = 0.0224
Ho: mean(diff) = 0	degrees of freedom = 307

Ha: mean(diff) < 0	Ha: mean(diff) != 0	Ha: mean(diff) > 0
Pr(T < t) = 0.5089	Pr(|T| > |t|) = 0.9821	Pr(T > t) = 0.4911

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95 % Conf. Interval]	
dEOS	308	.0061432	.0058466	.1026077	-.0053613	.0176477
dLTC	308	.0034301	.004325	.0759035	-.0050803	.0119405
Diff	308	.002713	.0074934	.1315089	-.0120319	.017458

mean(diff) = mean(dEOS - dLTC)	t = 0.3621
Ho: mean(diff) = 0	degrees of freedom = 307

Ha: mean(diff) < 0	Ha: mean(diff) != 0	Ha: mean(diff) > 0
Pr(T < t) = 0.6412	Pr(|T| > |t|) = 0.7176	Pr(T > t) = 0.3588