MOVING AVERAGES TRADING METHOD APPLIED TO CRYPTOCURRENCIES

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ABSTRACT

This research uses a popular investment technique called Moving Averages on crypto currencies. The 40 largest crypto currencies measured by market capitalization were evaluated. The research compares the returns of the crypto currencies using 5 of the commonly used parameter settings for the Moving Averages technique and compares these results to a buy-and-hold strategy. For some crypto currencies the Moving Averages technique outperformed the buy-and-hold technique. For others the buy-and-hold technique was the best.

KEYWORDS

Technical Analysis, Moving Averages, Cyptocurrency, Bitcoin, Blockchain

1.INTRODUCTION

Crypto currencies have provided lucrative investment options for investors willing to take extraordinary risk. Bitcoin alone has ranged from a few cents per Bitcoin to over $12,000. If an investor could capitalize on the sharp increases in price and avoid the drops, they could produce tremendous returns. We are beginning to see crypto currency hedge funds, mutual funds and individual investors. While the future of crypto currencies as an investment is uncertain currently some in the investment community are viewing them as a valid investment option.

Technical Analysis is a category of investing techniques in the area of Finance that uses Mathematical models of past market conditions to predict future market conditions [1-2]. Investors can use the future market prediction to place trades. Researchers are beginning to use Technical Analysis techniques that in the past were used to price stocks and bonds on crypto currencies. It is uncertain how these techniques will work in the crypto currency markets. This justifies research in this area [3].

The first crypto-currency was Bitcoin [4]. It is a decentralized currency that used Blockchain technology to keep a ledger of the currency transactions. Since the advent of Bitcoin over 1,000 crypto currencies have come into existence [5] . Each crypto currency uses a slightly different implementation which makes them unique enough to be separate currencies. Each crypto currency has a separate valuation and numerous exchanges have emerged to buy, sell and trade such crypto currencies. Coinbase.com, Binance.com, Abra.com and Kraken.com are some of the exchanges for crypto currencies.

One such Technical Analysis technique is the Moving Averages technique. The technique keeps track of two average prices of the security over two different periods of time. Buy and sell indicators are generated as the two averages surpass each other. While the technique does not always produce positive returns it is very popular being used on financial TV shows and in magazines. The research community has also shown interest in the technique and a number of research papers have been published on the technique.

This research applies the Moving Averages technique to the 40 largest crypto currencies as measured by market capitalization. Results of applying the technique are compared to a buy and hold strategy, which consists of just purchasing the crypto currency at the starting point and holding it until the ending point.

2.LITERATURE REVIEW

2 .1MOVING AVERAGES ALGORITHM

The Moving Average Rule keeps track of two easy to compute values using only the historical daily stock prices, which is easy and cheap to obtain. It computes a short term moving average and a long term moving average. The short term moving average is the average price of the stock over the last s days. The long term moving average is the average price of the stock over the last l days. It is implied by their names that $l > s$. The price of the stock is normally the daily close price.

The Moving Average Rule will generate buy and sell signals based upon these two moving averages. A *buy* signal is defined when the short term moving average passes above the long term moving average. Conversely, a *sell* signal is generated when the long term moving average passes above the short term moving average. It is normally impossible to time a buy or sell at the exact moment that the signals are generated. So, the general rule is that if the signal occurs on a given day the buy or sell will take place the following trading day.

There is a common issue with the Moving Averages Rules. Sometimes the buy and sell signals will oscillate very closely and generate many buy and sell signals over a short time frame. Since traders have to pay a trading fee for each transaction this can quickly erode profits. So a tolerance parameter is introduced as a percent. Now the buy or sell signals are generated when the moving averages exceed their percent tolerance. For a buy signal to be generated the short term moving average would have to exceed the long term moving average by this tolerance.
Moving Averages algorithms normally have three parameters in the format of (s, l, t). The parameters s and l are the number of days for the short term and long term moving averages respectively. The parameter t is the tolerance.

Here is an example shown in Figure 1. Here we see the Dow Jones Average index price in blue. The purple line is the 15-day moving average. The orange line is the 50-day moving average. Assuming that the tolerance is 0% and that we are using the stock's daily close prices, Table 1 indicates the buy and sells signals.

Fig. 1 Moving Averages Example

Table 1. Dow Jones Average with 15 day and 50 day moving averages.

Date	Trigger	Signal	Next Day Price	Return
10/15/2015	Short term passes long term	Buy	$17,215.97	
12/18/2015	Long term passes short term	Sell	$17,251.62	0.2071%
3/4/2016	Short term passes long term	Buy	$17,006.76	
5/19/2016	Long term passes short term	Sell	$17,435.40	2.52%

Certainly there is more research being conducting on stock investment strategies than what is being published. Many institutions keep their investment strategies carefully guarded secrets. They certainly would not publish their strategies and methods for a greater audience to learn. Most methods currently be researched are older methods that were originally published years ago. Compared to other stock investing strategies much research has been done on the Moving Averages technique. There is still debate as to the effectiveness of this method. Early research consists of [6] which concluded that the method did not outperform just buying the underlining stock and holding it. Little was published about the method until [7] found that the method could beat the approach of just buying the underlining stock. Researchers and investors still debate the effectiveness of the method.

Since this time most research has focused on using Moving Averages on specific markets, naming emerging markets. [8] Looked at stocks on the Barzilian stock market. [9] Evaluated stocks using the method on the Vietnamese stock market. [10] Used stocks on the Iran Tehran stock exchange. [11] Used the method on a number of stock markets in south-east Asia. [12] Tested the method on the Kuala Lumpur Stock Exchange. [13] Used the method on stocks in Asian stock exchanges. All of this research showed the method effective to different degrees.

One of the reasons that so much research has been done on this method is that there is no objective component to it; it is easy to program and the data is easy to locate. Daily stock data is freely downloadable on numerous financial websites. It is easy to compute the average using a custom written computer program and a spreadsheet. The method clearly shows entering and existing points for the trade.

2.2 Moving Average Method On Cryptocurrencies

There has been little if any research done using the Moving Average Method on Crypto currencies. Zhang [3] uses the Moving Average method accompanied by Logistic Regression to make trades. This research concludes that this hybrid method is profitable for trading in Bitcoin. Daniel [12] also conducted Moving Average research on Bit Coin. This research was only used on a set of parameters for the Moving Average method and did show positive performance. No research has been published on the larger Crypto currency market.

3.Data And Methodology

3.1.Data

This researched used the 40 top Crypto currencies measured by market capitalization when this research was conducted. Data was obtained at www.coinmarketcap.com. Table 2 contains this list of Crypto currencies along with the date range of the data and the total number of days within the date range. This range consists of all of the available prices at the time that data was extracted. The table is ordered in alphabetical order.

Table 2. Crytocurrencies Used in this Research

	Currency	From Date	To Date	# Days
1	Binance	7/25/2017	4/19/2018	269
2	Bitcoin	4/28/2013	4/19/2018	1,818
3	Bitcoin Cash	7/23/2017	4/19/2018	147
4	Bitcoin Diamond	11/24/2017	4/19/2018	179
5	Bitcoin Gold	10/23/2017	4/19/2018	41
6	Bitcoin Private	3/10/2018	4/19/2018	271
7	BitShares	7/21/2014	4/19/2018	1,369
8	Bytecoin	6/17/2014	4/19/2018	1,403
9	Bytom	8/8/2017	4/19/2018	255
10	Cardano	10/1/2017	4/19/2018	201
11	DASH	2/14/2014	4/19/2018	1,526
12	Dogecoin	12/15/2013	4/19/2018	1,587
13	EOS	7/1/2017	4/19/2018	293
14	Ethereum	8/7/2015	4/19/2018	987
15	Ethereum Classic	7/24/2016	4/19/2018	635
16	ICON	10/27/2017	4/19/2018	175
17	IOTA	6/13/2017	4/19/2018	311
18	Lisk	4/6/2016	4/19/2018	744
19	Litecoin	4/28/2013	4/19/2018	1,818
20	Maker	1/29/2017	4/19/2018	168
21	Monero	5/21/2014	4/19/2018	1,429
22	Nano	3/17/2017	4/19/2018	394
23	NEM	4/1/2015	4/19/2018	1,115
24	NEO	9/16/2018	4/19/2018	588
25	OmiseGO	7/14/2017	4/19/2018	280
26	Ontology	3/18/2018	4/19/2018	43

3.2 METHODOLOGY

The Moving Average algorithm described in the literature review can be implemented a number of ways using different assumptions. This research was conducted using the following conditions. Each purchase will be made of the exact same dollar amount. Once a purchase is made no other purchases will be made until there is a sell. Likewise, when a sell is made no other sells will be made until a purchase is made. At the end of the time frame any crypto currency held are not included in the results. This occurs because we do not know if those crypto currencies would be sold for a profit or loss.

Table 3 shows the parameters used in this research. These are the parameters used in the Brock, Lakonishok and LeBaron [7] research. Due to the low amount of data from currencies a tolerance of 0% was used. We did not see the problem of oscillation that the tolerance is meant to adjust for.

Table 3. Variable Moving Average Parameters Values

Test Case #	Short Term Moving Average (in days)	Long Term Moving Average (in days)	Tolerance
1	1	50	0%
2	1	150	0%
3	1	200	0%
4	2	200	0%
5	5	150	0%

4.RESULTS

Results are organized into three categories of Crypto currencies. For some Crypto currencies there simply was not enough data. Of the Crypto currencies that had enough data, in some cases the moving-average method beat the buy-and-hold method. The third group is the Crypto currencies in which the moving-average method did not beat the buy-and-hold method. Data in each group is shown in the tables below.

Tables are formatted with column headers consisting of the short term moving average followed by the long term moving average, example 1-50 represent short term moving average of 1 day with long term moving average of 50 days. Data within each cell is the total return as a percentage, followed by the number of trades in parentheses; example 694.6% (3) means there was a 694.6% return with 3 trades.

Tables 4 and 5 shows the Crypto currencies that did not produce any returns. For some of these there simply was not enough data, like Ontology which only had 43 days' worth of data. But others like Binance with 269 days' worth of data produce no trades for 1-150, 5-150, 1-200 and 2-200. The short term moving average never crossed the long term moving average. These Crypto currencies are reported in this research for completeness.

Table 4. Crytocurrencies in which there is not enough data for the Moving Average Method.

Currency	1-50	1-150	5-150	Buy and Hold
Binance	694.6% (3)	0.0% (0)	0.0% (0)	11,499.1%
Bitcoin Diamond	-185.8% (3)	0.0% (0)	0.0% (0)	-95.9%
Bitcoin Gold	-21.8% (3)	0.0% (0)	0.0% (0)	-89.0%
Bitcoin Private	0.0% (0)	0.0% (0)	0.0% (0)	-56.2%
Bytom	255.0% (5)	0.0% (0)	0.0% (0)	731.9%
ICON	90.3% (2)	0.0% (0)	0.0% (0)	539.8%
Maker	22.5% (1)	0.0% (0)	0.0% (0)	3,324.9%
Ontology	0.0% (0)	0.0% (0)	0.0% (0)	50.4%
Wanchain	0.0% (0)	0.0% (0)	0.0% (0)	41.8%
Zilliqa	-8.7% (1)	0.0% (0)	0.0% (0)	-51.5%

Table 5. Crytocurrencies in which there is not enough data for the Moving Average Method.

Currency	1-200	2-200	Buy and Hold
Binance	0.0% (0)	0.0% (0)	11,499.1%
Bitcoin Diamond	0.0% (0)	0.0% (0)	-95.9%
Bitcoin Gold	0.0% (0)	0.0% (0)	-89.0%
Bitcoin Private	0.0% (0)	0.0% (0)	-56.2%
Bytom	0.0% (0)	0.0% (0)	731.9%
ICON	0.0% (0)	0.0% (0)	539.8%
Maker	0.0% (0)	0.0% (0)	3,324.9%
Ontology	0.0% (0)	0.0% (0)	50.4%
Wanchain	0.0% (0)	0.0% (0)	41.8%
Zilliqa	0.0% (0)	0.0% (0)	-51.5%

Tables 6 and 7 show the Crypto currencies for which the moving-average method generally outperformed the buy-and-hold method. In some cases, small moving-average parameter beat buy-and-hold, but not larger ones. Bit Shares beat its buy-and-hold return for 1-50, 1-150 and 5-150, but did not for 1-200 and 2-200. In other case, like Lisk, all parameter values beat the buy-and-hold method.

Table 6. Cryptocurrencies in which Moving Average Method beats the buy-and-hold Method.

Currency	1-50	1-150	5-150	Buy and Hold
BitShares	4,884.9% (30)	2,378.1% (13)	1,929.5% (10)	1,587.7%
EOS	1,276.1% (1)	125.2% (2)	123.3% (1)	794.1%
IOTA	415.1% (3)	160.8% (3)	148.9% (2)	186.3%
Lisk	1,469.3% (15)	8,914.7% (1)	8,458.3% (1)	200.0%
Litecoin	1,883.6% (45)	4,200.7% (22)	3,907.5% (15)	3,118.4%
NEO	17,175.7% (18)	44,976.6% (2)	42,828.0% (1)	12,942.6%
Populous	983.0% (4)	-16.8% (1)	-24.7% (1)	605.1%
Steem	1,243.6% (12)	687.9% (3)	568.9% (3)	244.1%
Stellar	3,836.4% (31)	869.0% (23)	762.9% (15)	1,4307.5%
Zcash	576.7% (11)	258.6% (5)	219.0% (4)	-87.9%

Table 7. Cryptocurrencies in which Moving Average Method beats the buy-and-hold Method.

Currency	1-200	2-200	Buy and Hold
BitShares	1,324.6% (12)	1,312.5% (11)	1,587.7%
EOS	-50.0% (1)	-50.0% (1)	794.1%
IOTA	-54.2% (1)	-54.2% (1)	186.3%
Lisk	6,178.6% (2)	6,628.5% (1)	200.0%
Litecoin	3,352.6% (20)	3,254.5% (16)	3,118.4%
NEO	27,777.6% (2)	29,576.5% (2)	12,942.6%
Populous	-76.2% (1)	-76.2% (1)	605.1%
Steem	474.5% (3)	452.5% (2)	244.1%
Stellar	949.7% (19)	955.1% (17)	1,4307.5%
Zcash	134.4% (4)	145.4% (2)	-87.9%

Table 8 and 9 shows the Cryptocurrencies in which the buy-and-hold method generally beat the moving-average method. In some cases, the difference between the methods was large. The buy-and-hold method for Ethereum produced an 18,845.5% return, but the best moving-average method only produced a 6,570.9% return. DASH's buy-and-hold produced a return of 113,732.4% return compared to the best moving-average method of 5,355.6% return. Other Cryptocurrencies were closer. Dogecoin's buy-and-hold method produced a 1,716.1% return while it is best moving-average return was 1,646.5% return.

Table 8. Cryptocurrencies in which the buy-and-hold Method beats the Moving Average Method.

Currency	1-50	1-150	5-150	Buy and Hold
Bitcoin	775.5% (32)	3,684.9% (10)	3,427.6% (7)	5,982.6%
Bytecoin	1,058.7% (32)	2,301.5% (26)	497.3% (17)	7,345.0%
Bitcoin Cash	239.2% (3)	-74.5% (2)	-95.5% (2)	115.2%
Cardano	1,698.2% (1)	-6.1% (1)	-4.8% (1)	942.6%
DASH	1,931.3% (30)	5,355.6% (11)	4,078.6% (7)	113,732.4%
Dogecoin	1,646.5% (31)	697.9% (20)	680.8% (12)	1,716.1%
Ethereum	3,479.3% (17)	6,467.2% (8)	6,570.9% (7)	18,845.5%
Ethereum Classic	1,252.4% (7)	508.7% (3)	540.5% (3)	1,797.0%
Monero	969.0% (29)	3,798.2% (19)	4,014.7% (11)	14,171.9%
Nano	15,416.6% (5)	4,882.6% (1)	5162.3% (1)	72,637.8%
NEM	6,398.4% (19)	7,660.3% (8)	6,898.3% (6)	155,134.7%
OmiseGO	42.0% (7)	-8.6% (2)	27.3% (2)	2,478.6%
Qtum	110.7% (6)	50.7% (5)	114.4% (3)	183.5%
Ripple	4,616.8% (33)	2,435.8% (24)	2,291.1% (16)	11,952.6%
Siacon	4,249.2% (17)	3,174.6% (10)	3,239.2% (7)	46,807.3%
Stratis	6,473.6% (18)	6,791.1% (5)	7,906.5% (3)	50,101.3%
Tether	-23.4% (44)	-19.1% (40)	-12.2% (23)	-17.6%
TRON	2,107.9% (2)	-46.8% (3)	-54.8% (2)	2,290.4%
VeChain	1,184.3% (4)	-57.5% (2)	-59.1% (1)	1,319.1%
Verge	8,738.0% (48)	167,205.5% (34)	181,270.5% (17)	928,414.3%

Table 9. Cryptocurrencies in which the buy-and-hold Method beats the Moving Average Method.

Currency	1-200	2-200	Buy and Hold
Bitcoin	2,693.2% (9)	3,035.1% (8)	5,982.6%
Bytecoin	437.4% (28)	481.7% (22)	7,345.0%
Bitcoin Cash	-15.0% (1)	-16.8% (1)	115.2%
Cardano	0.0% (0)	0.0% (0)	942.6%
DASH	4,228.2% (9)	4,942.4% (6)	113,732.4%
Dogecoin	567.9% (15)	484.0% (12)	1,716.1%
Ethereum	5,097.4% (4)	5,113.4% (3)	18,845.5%
Ethereum Classic	718.7% (7)	753.1% (6)	1,797.0%
Monero	4,1044.3% (14)	41,519.4% (14)	14,171.9%
Nano	7,626.3% (1)	7,626.3% (1)	72,637.8%
NEM	6,008.9% (7)	5,940.5% (7)	155,134.7%

OmiseGO	-20.0% (2)	-24.2% (1)	2,478.6%
Qtum	98.5% (1)	81.3% (1)	183.5%
Ripple	2,883.3% (16)	2,924.9% (14)	11,952.6%
Siacon	1,727.9% (6)	1,666.9% (5)	46,807.3%
Stratis	4,891.6% (6)	4,772.0% (5)	50,101.3%
Tether	-17.2% (36)	-23.0% (31)	-17.6%
TRON	-6.3% (1)	0.0% (0)	2,290.4%
VeChain	-43.8% (2)	-51.3% (2)	1,319.1%
Verge	125,140.3% (26)	125,251.2% (20)	928,414.3%

5.CONCLUSIONS

In summary we performed the Moving Averages trading technique on the top 40 cryptocurrencies comparing the returns against a buy-and-hold strategy. In some cases, we determined that the Moving Averages strategy outperformed the buy-and-hold strategy. This allowed investors to buy while the currency was going up and sell it before losses were incurred when the currency was going down. For these currencies most of the parameter values produce superior results to the return for the buy-and-hold strategy. But these were rare cases; only 10 out of the 40 cryptocurrencies tested fell into this category.

Another 10 cryptocurrencies were categorized as not having enough data to determine the effectiveness of the Moving Averages strategy. Surprisingly some of the cryptocurrencies with the largest market capitalization have not been around long enough to use the Moving Averages method. There simply wasn’t enough data from the cryptocurrency exchange to make any purchases. In other cases, the Moving Averages method never generated the initial buy indicator. Since the Moving Averages method assumes that you begin without owning any investments, at some point in time you need the short term moving average to pass the long term moving average. And in some cases that never happened.

Half of all cryptocurrencies fell into the final category. The buy-and-hold strategy outperformed the Moving Averages strategy. This included the most popular cryptocurrency, Bitcoin. The Moving Averages strategy returned between 775.5% to 3,684.9% for Bitcoin, depending upon the parameter values selected. The buy-and-hold strategy returned 5,982.6% for Bitcoin. Our research indicates that for a vast majority of cryptocurrencies the Moving Averages strategy would not be beneficial.

This research makes some assumptions. It assumes that a cryptocurrencies will always be in one of the three categories and not change. This is a limitation of this research. It is possible that cryptocurrencies be in different categories for different time periods.

We have a number of observations and hypothesis developed from this work that could make future research. First, it is possible that the benchmark parameter values that have been used for decades in Moving Averages research on stock do not apply to cryptocurrencies. We may need to develop a new set of benchmark parameter values for cryptocurrencies. Second, for some cryptocurrencies the Moving Averages strategy worked very well. It is not known if they consistently do well with this strategy. Replication studies need to be done in the future to determine if these cryptocurrencies consistently do well with the Moving Averages strategy. Third, other technical analysis trading strategies should be applied to cryptocurrencies. These topics would make good future research.

The Moving Averages trading strategy does not outperform the buy-and-hold strategy for most cryptocurrencies. However, for some cryptocurrencies it produces superior returns. For these cryptocurrencies the strategy could reduce risk and increase return for investors.

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