An Investigation into the Momentum Anomaly in the Market for Bitcoin

Abstract
This paper examines the momentum anomaly with regard to daily returns on the bitcoin market from *23/07/2010 to 06/03/2013. The study represents a test of the efficiency of the market with an emphasis on the role of behavioural factors in explaining the anomaly. A combination of stationarity and autocorrelation tests was used to examine whether bitcoin satisfies the weak form of the Efficient Market Hypothesis. It was concluded that bitcoin returns do not follow a random walk and the time series exhibits predictability. Further analysis of the autocorrelation tests revealed substantial evidence of momentum in daily bitcoin returns in addition to other peculiarities.*

Introduction

The analysis of the efficiency of financial markets is one of the topics that has received most attention in the empirical literature of economics. The usual approach is to examine the predictability of stock price returns using tests for stationarity and autocorrelation. Further, Jeegadesh and Titman's (1993) "strength rule" strategy has been used in many studies to test for the presence of the momentum effect. This has been done using different types of data sets depending on data availability and the objectives of the study.

Most of these studies have tested for momentum by examining returns on stocks with high returns over the previous 3-12 months. Jegadeesh and Titman (1993) document that, strategies which buy these long term winners and sell long term losers earn profits of about one per cent per month for the following year. Thus the prevailing discussion has centred on studies using low frequency data over long horizons. Consequently, evidence of momentum in daily returns has been very limited. In this paper, I try to bring new evidence to bear on the empirical issue by using high frequency data and making use of a dataset corresponding to the bitcoin[1] market; one of this year's most publicized financial assets. The first section outlines some of the background economic theory motivating this study and the rationale behind focusing on bitcoin. This will be followed by a description of the empirical approach and a discussion of the estimation results.

Theory & Rationale

The Efficient Market Hypothesis is a staple of standard finance theory. A financial market is said to be informationaly efficient if current prices fully reflect all available information. Jensen (1978) described this concept compactly;

"A market is efficient with respect to information set θ_t if it is impossible to make economic profits by trading on the basis of information set θ_t" (Jensen, 1978 p. 3)

Fama (1970) identified three levels of market efficiency: weak; semi-strong; and strong, each differing with respect to the relevant definition of 'information'. Weak form efficiency refers to the information set containing historical data; semi strong efficiency examines all publicly available information whilst strong efficiency looks at all available information. These three forms can be differentiated under by Jensen's definition by changing the "θ_t" term.

The concept of a random walk is central to the EMH. Fama (1965, p.34) states that the random walk implies that "successive price changes are independent, identically distributed random variables" and in an efficient market "stock prices follow random walks and at every point in time actual prices represent good estimates of intrinsic values" and prices will over-adjust as often as they will under-adjust (Fama, 1965, p.40). In this regard, the weak form EMH suggests that past returns will be uncorrelated with present returns and no profitable strategy can be implemented by examining past returns.

The EMH has not been without its critics. Shiller (1981, p.459) states that the argument that share prices represent good estimates of intrinsic values at every point in time "represents one of the most remarkable errors in the history of economic thought". The empirical validity of the EMH has been called into question by a series of anomalies. For example, the existence of price bubbles is incompatible with the idea of efficient markets as the presence of arbitrageurs should drive prices to fundamental value. Furthermore, Shiller and others have shown that equity returns are excessively high and volatile. The existence of these anomalies allows for the possibility of profiting from available information, which the EMH of course, does not allow.

[1] Unlike traditional currency, which is issued in digital and physical form by governments, bitcoin exists only online and is maintained by a decentralized network of computers, called "miners," which create new bitcoins and verify transactions. Once created, bitcoins can be traded on currency exchanges or used as money to purchase goods and services from merchants that accept it (Light 2013)

Such anomalies have been grouped as fundamental and calendar anomalies. Calendar anomalies refer to the possibility that returns will vary depending on the day of the week or time of year. Two of the most famous are the “January Effect” and the “Monday Effect”. (Keim 1983)These effects have been eliminated in most modern markets due to technological advancement or perhaps the effects of being publicized. One fundamental anomaly namely the momentum effect continues to defy explanation. It is this anomaly which will be the principal focus of our study. The momentum effect refers to the tendency for stocks which have performed well in the short term to perform well in the subsequent period. (O’Keefe, 2013) The effect implies a continuation in returns and positive serial correlation in abnormal returns. Levy (1967, p.609) concludes that “superior profits can be achieved by investing in securities which have historically been relatively strong in price movement”. Jegadeesh and Titman (1993) find that a strength rule strategy, which involves buying past winners and selling past losers, generates significant abnormal returns in the US. Momentum has also been found with European stocks, (O’Keefe 2013, p31) reports, “Momentum has also been well documented in European Markets on a country by country basis for Italy (Mengoli, 2004), Sweden (Parmler and Gonzalez, 2007… and Germany (Schiereck *et al.* 1999; Glaser and Weber, 2003). Significant momentum returns are discovered in the UK by, *inter alios*, Siganos (2010); Galariotis *et al.* (2007); and Aarts and Lehnert (2005)”.

Previous literature on the link between Bitcoin and the EMH is limited, however some authors have pointed out the impossibility of an asset like bitcoin under efficient markets. For example Nielsen, 2013 says “it (Bitcoin) deals a blow to the Efficient Market Hypothesis by following a trend that cannot be called random. Its extreme volatility should dispel any illusion that investors have rational expectations and believe the long term price of bitcoin is $261 one day, $50 the next, $150 the next and $100 the day after that”. As such it has been suggested that Bitcoin does not satisfy weak form EMH.

Using casual observation, I have noticed that momentum may be a property of bitcoin returns and as a result wish to investigate it formally. Further, the extreme volatility in daily returns allows for the possibility of documenting momentum using high frequency short term data. If the momentum anomaly is observed it may be possible to make abnormal profits using past bitcoin price data alone, for someone with an interest in financial markets this is an exciting prospect.

Some readers may question the importance of bitcoin on a macro scale, and subsequently whether this paper’s results are economically significant. Bitcoin has certainly garnered mixed opinions from economists with many labelling it a “bubble”[2]. Robert Shiller, writes in the New York times this month "The bitcoin phenomenon seems to fit the basic definition of a speculative bubble — that is, a special kind of fad, a mania for holding an asset in expectation of its appreciation," whilst Alan Greenspan noted in a Bloomberg Television interview last December. “It (a currency) has to have intrinsic value. You have to really stretch your imagination to infer what the intrinsic value of bitcoin is. I haven’t been able to do it. Maybe somebody else can.”

However, are they writing bitcoin off too soon? John Authers wrote in the Financial Times last December, “This month has seen notes on the online currency from mainstream foreign exchange analysts at Wall Street banks Citi and BofA Merrill Lynch. When Wall Street has to take bitcoin seriously, the online currency has arrived.” This author in addition to many others believes bitcoin will be the leading mechanism for online and mobile payments in the near future. If this were to materialise, its independence from government control would make bitcoin a very influential financial asset. In the next section we present specification of the empirical approach followed by a discussion of the estimation results.

Methodology

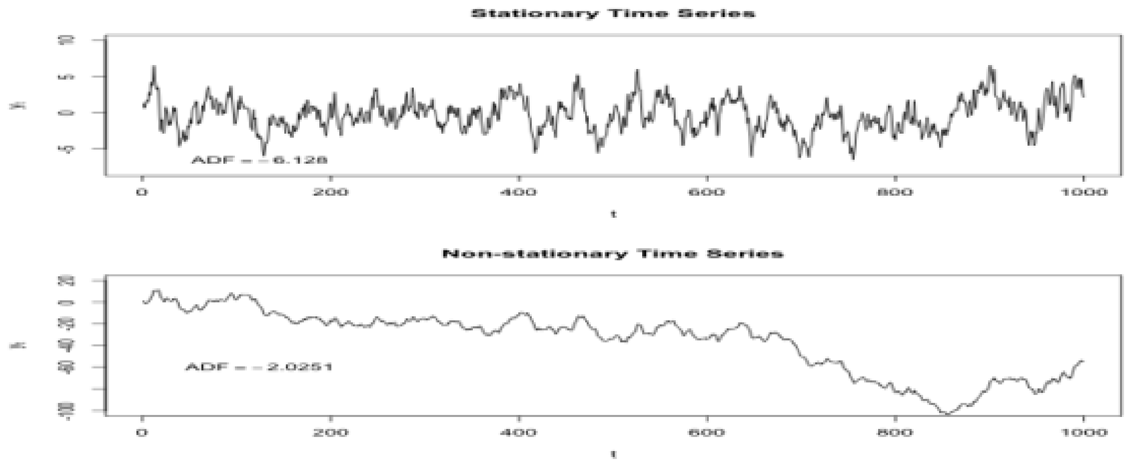
If Bitcoin is an efficient market; returns will follow a random walk. That is, it will not be possible to identify a pattern in price movements. We will consider the hypothesis that returns on daily Bitcoin prices follow a random walk using some common tests of stationarity. Returns were calculated using daily Bitcoin closing prices with:

$$R_{mt} = Ln(\frac{BTC_t}{BTC_{t-1}})$$

Where R_{mt}= daily logarithmic return on Bitcoin, BTC_t= Bitcoin closing price day t and BTC_{t-1}= Bitcoin closing price on day t-1. I have chosen to use logarithmic returns as it increases the likelihood that the returns are distributed normally which is a prerequisite of the Random Walk Hypothesis (Mobarek & Keasey, 2000). To test whether our returns do indeed follow a random walk I will perform both the Augmented Dickey Fuller test and the Runs test. The concept of stationarity refers to a time series process where the distribution of a process doesn’t change over time. Therefore a stochastic process is said to be stationary when it’s mean,

[2] $13.51/BTC in January 2013 to $1242/BTC November 2013

variance and covariance do not change throughout the time series. Stationarity can sometimes be determine visually. For example figure 1 shows a stationary series (top), in comparison with a non-stationary series. (Dixon 2005)



1) Dickey Fuller Test
The Dickey Fuller test is designed to test whether a series possesses a unit root or is trend stationary. If the process is found to be trend stationary, it may be possible to predict price changes from past prices. I will run the following regression in order to perform this test

A) $\Delta R_{mt} = (\rho - 1)R_{mt-1} + u_t$

If the coefficient on R_{mt-1} is equal to zero the process has a unit root and we can say we have a difference stationary process, if it is less than zero our process is trend stationary. As such the hypotheses are:

H_o: (ρ - 1) =0 – the process is difference stationary
H_a: (ρ - 1) <0 – the process is trend stationary.

If we can reject this null hypothesis, we have evidence that returns do not follow a random walk and may be predictable. (Dixon 2005)

2) Runs Test
The runs test can also be used to examine whether a series follows a random walk. A runs test examines the number of runs which are present in a series and compares this to the number of runs which would be expected for the sample size. A run is defined as follows:

“a succession of identical symbols which are followed or preceded by different symbols or no symbol at all” (Siegal, 1956 p. 52)

If the number of runs observed is sufficiently different than the number expected we will have evidence against the series being random. The runs test z-statistic allows us to examine the null hypothesis that this series is a random one. If Bitcoin prices are to display momentum we would expect there to be fewer runs in the series than would be expected. A rejection of the null hypothesis would give us further evidence that Bitcoin returns are predictable. The runs test has several advantages; firstly it does not require the series to be normally distributed (Mobarek & Keasey, 2000). Another benefit of the runs test is that where the majority of other tests examine correlation coefficients in their studies of the ability to use past returns to predict current returns run tests do not. This is convenient as correlation coefficients can be heavily influenced by extreme observations which will create bias in the test. Thus run tests are a convenient way for adjusting for any outlier observations (Elton et al, 2011)

3) Autoregressive Test
We have next included a basic Autoregression test to see if daily returns in the present period are correlated with past returns. Using OLS I will examine:

1) $R_{mt} = B_0 + B_1 R_{mt-1} + B_2 R_{mt-2} + B_3 R_{mt-3} + B_4 R_{mt-4} + B_5 Gold + B_6 Oil + B_7 Silver + B_8 Newposts + e_t$

This regression will examine whether returns are correlated with returns from previous periods. We have included the daily price of oil, gold and silver as control variables. As gold oil and silver are independent stores of value similar to what many envisage for bitcoin, we expect these variables to move together with bitcoin. We have also included the control variable *Newposts* which is the number of posts daily on Bitcoin news forum BitcoinTalk. This is to control for the impact of publicity on bitcoin prices, we expect that the more people who find out about bitcoin the more demand there will be for it. If any of our B_i on past returns' are found to be statistically significant and different from zero, we will have evidence against the efficient market hypothesis and allow for the possibility of predicting present returns based on past returns. If our series is to display a momentum effect we would expect present returns to display positive correlation with past returns, i.e. positive B_i.

4) Dummy Variable Analysis
As a basic test of whether momentum is a feature of our model I will run the following OLS regressions using dummy variables:

1) $R_{mt} = B_0 + \delta x_1 + \delta x_2 + \delta x_3 + \delta x_4 + \delta x_5 + B_1 Gold + B_2 Oil + B_6 Silver + B_7 Newposts + e_t$

2) $R_{mt} = B_0 + \delta z_1 + \delta z_2 + \delta z_3 + \delta z_4 + \delta z_5 + B_1 Gold + B_2 Oil + B_6 Silver + B_7 Newposts + e_t$

Where:
x_1 = positive return in previous period
x_2 = positive return for two previous periods in a row
x_3 = positive return for three previous periods in a row
x_4 = positive return for four previous periods in a row
x_5 = positive return for five previous periods in a row

z_1 = negative return in previous period
z_2 = negative return for two previous periods in row
z_3 = negative return for three previous periods in row
z_4 = negative return for four previous periods in row
z_5 = negative return for five previous periods in row

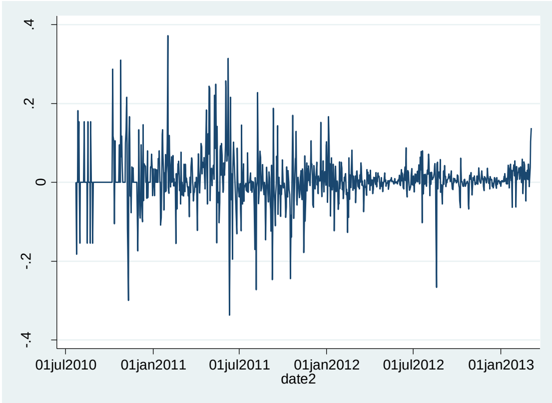
If any of our dummies are found to be statistically significant and different from zero we have found evidence against weak form efficiency as prices can seemingly be predicted from historical data. If momentum is to be present we would expect positive coefficients on our x_i dummies as a prices rise on day t-1 will be followed by price rise on day t. Similarly we expect a negative coefficient on our z_i dummies as price falls are likely to be followed by a further price fall. We will run these two regressions separately as "negative return in previous period" is of course highly negatively correlated with "positive return in previous period".

5) Momentum Trading strategy
Finally we will use a basic momentum trading strategy to analyse profitability over a sample period. For this I will draw a random sample of 100 consecutive daily prices from our data set. We will use a simple strength rule strategy by buying bitcoin when the price rises and then selling it when the price falls. We will examine the return on a $100 investment and compare this to the return on the traditional buy and hold strategy. I will then use the same strategy using monthly data to examine the effect of using lower frequency data.

Dataset
For this study I used the daily closing price for Bitcoin on the Tokyo based MTGOX exchange from 23/07/2010 to 06/03/2013. This data was downloaded from www.bitcoincharts.com raw data source. This allowed me to calculate 955 returns for the period, giving me 952 observations. Graph 1and 2 below give a view of the trend of both daily return on Bitcoin and MTGOX Bitcoin price over the period studied. Returns have been extremely volatile with a huge upward trend in price. This explains the positive mean on returns shown over the time period. Daily prices for Gold (100oz), Silver and Crude Oil (WTI)(barrel) over the same time period were downloaded from the Reuters data stream service available in the Trinity College library. Number of new posts on BitcoinTalk was also gathered from www.bitcoincharts.com.

Graph (1) Price

Graph (2) Return



Empirical Results

1) Augmented Dickey Fuller Test

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-12.276	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.0000

D.Return	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Return						
L1.	-.752848	.0613267	-12.28	0.000	-.8732017	-.6324943
LD.	.0406738	.0551507	0.74	0.461	-.0675596	.1489071
L2D.	-.0669236	.0481754	-1.39	0.165	-.1614679	.0276206
L3D.	-.0654557	.0400718	-1.63	0.103	-.1440968	.0131853
L4D.	-.0971243	.0323646	-3.00	0.003	-.1606399	-.0336086
_cons	.0053758	.0019412	2.77	0.006	.0015661	.0091855

Here we can overwhelmingly reject the null hypothesis of a unit root at all common significance levels. From the regression output, the estimated β of -0.75 implies that ρ = (1-0.75) = 0.25. Experiments with fewer or more lags in the augmented regression yield the same conclusion. This suggests our returns follow a trend stationary process; in this regard they are not a random walk and may be predictable based on past returns. This is evidence against the weak form efficient market hypothesis and leaves open the possibility of profiting from historical price data.

2) Runs Test

```
. runtest Return, thresh(0)
 N(Return <= 0) = 476
 N(Return >  0) = 476
            obs = 952
        N(runs) = 350
             z  = -8.24
       Prob>|z| = 0
```

The p-value, 0, of this test statistic tells us that we can reject the null hypothesis that this series is a random one at any common significance level. The significant negative Z value informs us that the number of runs is lower than the expected number. This indicates that there is positive serial correlation present with respect to the return series. Thus we can conclude that this series is not in fact a random series and that the study of past returns can help to predict the current level of returns. This backs up the result from the Augmented Dickey Fuller test that the bitcoin market does not satisfy the weak form of the EMH. The negative z-stat backs up our claim that momentum may be a feature of bitcoin returns as it indicates a tendency for a positive change to be followed by another positive change and negative change to be followed by another negative change.

3) Autoregression test

Before interpreting the results a number of robustness checks where necessary. I tested for the presence of heteroskedasticity in the errors using the Breusch- Pagan test and Whites test. The Breusch-Pagan found no evidence of heteroskedasticity at any practical significance level. However this test only tests for the linear form of heteroskedasticity so we also ran Whites LM test, which is a more general test of heteroskedasticity. Whites test gave a p-value of 0.0000 and thus rejected the Null hypothesis of homoscedastic errors at the 1% level. This tells us that our errors are heteroskedastic. If ignored this would give us biased results, we therefore must correct for it by using robust standard errors in our regressions.

1st Regression

```
Linear regression                               Number of obs =     952
                                                F(  6,   945) =    7.57
                                                Prob > F      =  0.0000
                                                R-squared     =  0.0837
                                                Root MSE      =  .05877
```

Return	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
Return_1	.2544301	.0494635	5.14	0.000	.157359	.3515011
Return_2	-.1016965	.0501356	-2.03	0.043	-.2000864	-.0033066
Return_3	-.0193969	.055872	-0.35	0.729	-.1290445	.0902506
Return_4	-.0149897	.0405538	-0.37	0.712	-.0945757	.0645963
Gold	-.0000444	.0000137	-3.23	0.001	-.0000713	-.0000174
Oil	.000675	.0002219	3.04	0.002	.0002395	.0011105
_cons	.0133622	.0256672	0.52	0.603	-.0370092	.0637336

As can be seen we have found a positive relationship between returns in period t and period t-1 which is significant at a 1% significance level. The coefficient of 0.254 on R_{mt-1} in the regression tells us that a 1% increase in returns in time t-1 will cause a 0.254% increase in returns in time t. This is further evidence against weak form efficiency and suggests prices can be predicted from past prices. The positive coefficient on R_{mt-1} is also in keeping with our momentum theory. Interestingly the relationship is reversed when returns from further back are examined. The relationship between R_{mt-2} and R_{mt} is negative and significant at a 5% level, from our model an increase in returns of 1% two days ago will cause returns today to fall by 0.1%.

The positive but less than unity coefficient on Return_1 displays the underreaction theory of momentum described earlier quite well. Shleifer (2000) says that good news, (such as for example a large retailer accepting bitcoin as payment) will not immediately be fully incorporated into the price. This has been somewhat attributed to conservatism bias amongst investors described by Edwards (1968) “Conservatism states that individuals are reluctant or slow to change their prior beliefs in the face of new information”. Prices will therefore only slowly fully adjust to the good news as investor’s reform their beliefs. As a result, excess returns are expected for a period of time after good news. Previous studies such as Jegadeesh and Titman (1993) have found this period to be anywhere between 3 weeks and 2 years in some cases. Bitcoin seems to react much faster though as the positive autocorrelation only lasts for one day. There is a negative relationship after two days and then insignificance from then on. This relationship also seems to rule out the alternative theory of positive feedback traders. Interestingly this may provide evidence that Bitcoin is not a price bubble.

The negative relationship observed between returns in day t and day t-2 may be explained by the overreaction hypothesis. (Li and Yu 2009 p7) state “(this) stock price overreacts to a series of news, leading to reversal in subsequent returns in longer horizons”. This effect has been attributed to the representative heuristic, this is the idea that investors will believe future patterns will resemble past patterns and as a result overreact to trends. (Shleifer 2000) After good news our model predicts excess returns for today and tomorrow, investors on the third day may then overreact to this apparent trend and overvalue bitcoin. These investors will then experience negative returns as prices fall to fundamental value by close of day three. The insignificance of returns from further periods back is also in keeping with theory which suggests that after the initial underreaction and eventual overreaction, prices stabilise and past returns no longer have an effect. Most studies however find this overreaction only occurs over long horizons, Debondt and Thaler (1985) find that “portfolios of stocks with extremely poor returns over the previous 5 years significantly outperform portfolios of stocks with extremely high returns”. With bitcoin it seems to happen after only two days. This, may be a result of misspecification in our or model or alternatively may indicate an abnormality unique to bitcoin. Perhaps the significant presence of noise traders[3] and very low transaction costs within the bitcoin market may cause the overreaction to happen much sooner.

As can be seen our control variables Gold and Oil are both significant at the 1% level, this is to be expected as investors are likely to use these prices as a benchmark. Interestingly their coefficients have different signs,

[3] The term used to describe an investor who makes decisions regarding buy and sell trades without the use of fundamental data

returns on bitcoin seemingly fall when Gold prices rise and rise when Oil prices rise. An explanation for this is beyond the scope of this paper however it may suggest that investors see Oil as a more similar store of value to bitcoin than Gold is. Control variables, Silver and Newposts have been excluded from the final regression as they have been found to be very insignificant in previous regressions.

4) Dummy Variable Analysis

1st Regression

```
Linear regression                                    Number of obs =      952
                                                     F(  7,   944) =     6.73
                                                     Prob > F      =   0.0000
                                                     R-squared     =   0.0576
                                                     Root MSE      =   .05964
```

Return	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
oneday	.0207003	.0044545	4.65	0.000	.0119584	.0294423
twodays	.0053153	.0060803	0.87	0.382	-.0066172	.0172479
threedays	-.0026035	.0089381	-0.29	0.771	-.0201444	.0149373
fourdays	.0067308	.0123875	0.54	0.587	-.0175793	.031041
fivedays	-.0032112	.0130426	-0.25	0.806	-.028807	.0223845
Gold	-.0000605	.0000144	-4.20	0.000	-.0000888	-.0000323
Oil	.0005704	.0002293	2.49	0.013	.0001205	.0010204
_cons	.0374833	.0251007	1.49	0.136	-.0117763	.086743

2nd regression

```
Linear regression                                    Number of obs =      952
                                                     F(  7,   944) =     5.85
                                                     Prob > F      =   0.0000
                                                     R-squared     =   0.0487
                                                     Root MSE      =   .05992
```

Return	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
neg_oneday	-.0268347	.0060029	-4.47	0.000	-.0386154	-.015054
neg_twodays	.0152301	.0081918	1.86	0.063	-.0008462	.0313063
neg_threedays	-.0111989	.0130556	-0.86	0.391	-.0368203	.0144226
neg_fourdays	.0037459	.0146764	0.26	0.799	-.0250562	.0325481
neg_fivedays	-.0000978	.0170459	-0.01	0.995	-.0335501	.0333545
Gold	-.0000414	.000014	-2.97	0.003	-.0000688	-.000014
Oil	.0008544	.000241	3.55	0.000	.0003814	.0013274
_cons	-.000091	.0257121	-0.00	0.997	-.0505504	.0503685

The Breusch Pagan test indicated the presence of heteroskedasticity in both regressions with p=0.0001 and p=0.0472, these results were confirmed by whites test. As a result we have used robust standard errors in both regressions. Both regressions were also checked for underspecification using Ramsey as before, with F=0.074 and 0.42 we have no evidence of underspecification or omitted variable bias. The sign of the price change yesterday should have no effect on return today under efficient markets. As can be seen, this does not seem to be the case with bitcoin. Both our positive one day dummy and negative one day dummy are different from zero and significant at the 1% level. This was expected given previous results and gives more evidence against weak form efficiency for Bitcoin. The sign of both of our coefficients is in keeping with our theory of momentum. From our model a positive price change yesterday will increase returns today by 0.021 on average. Similarly a negative price change yesterday will cause returns to fall by 0.0268 today. From this result it seems possible to profit on bitcoin by simply buying the currency when the price goes up. The coefficients are very close together however it seems investors react more to price falls than price rises. This may indicate a fear from investors that bitcoin may be a bubble ready to burst and therefore are eager to exit once the price shows weakness. We also included dummies which capture further strings of positive and negative price changes. As can be seen oneday and neg_oneday are the only significant dummies at the 5% level. Neg_twodays is however significant at a 7%

level but with a positive coefficient, this back's up our claims that investors may overreact after the initial momentum has passed and overestimate bitcoins value, this result suggests that a price fall two days ago will lead to an increase of 0.015 in returns today.

5) Momentum Strategy

	Price	Momentum Strategy			No. of Bitcoins bought	Cash from Sale	Buy and Hold Strategy			No. of Bitcoins bought	Cash from Sale
5/30/2012	**5.11**	BUY			19.5694716		BUY			19.569472	
5/31/2012	**5.14**		HOLD					HOLD			
06/01/2012	**5.16**	BUY						HOLD			
06/02/2012	**5.18**		HOLD					HOLD			
06/03/2012	**5.27**		HOLD					HOLD			
06/04/2012	**5.25**			SELL		102.69		HOLD			
06/05/2012	**5.21**		HOLD					HOLD			
06/06/2012	**5.27**	BUY			19.49			HOLD			
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8/29/2012	**10.90**			SELL		213.64		HOLD			
8/30/2012	**10.84**		HOLD					HOLD			
8/31/2012	**10.76**		HOLD					HOLD			
09/01/2012	**10.18**		HOLD					HOLD			
09/02/2012	**10.00**		HOLD					HOLD			
09/03/2012	**10.05**	BUY			21.2577114			HOLD			
09/04/2012	**10.35**		HOLD					HOLD			
09/05/2012	**10.30**		HOLD					HOLD			
09/06/2012	**10.75**		HOLD					HOLD			
09/07/2012	**10.94**			SELL		232.55			SELL		214.06
	Return					132.55%					114%

Given the results of previous tests, it now seems plausible to make abnormal returns using a momentum trading strategy on the bitcoin market. We used a basic strength rule strategy over the 101 day period between 05/30/2012 and 09/07/2012. The table above gives an outline of the strategy used by showing the first 8 days and last 10 days of trading. As Bitcoin's price has risen consistently over the past 3 years, it is likely any trading strategy would be profitable. Our momentum trading strategy however clearly outperforms the regular buy and hold strategy with returns of 132.55%, this is almost 20% higher than a simple buy and hold strategy.

We also tested our theory using lower frequency data. Monthly returns were calculated over a two year period and a similar momentum trading strategy was applied, i.e. if positive change in returns in January, buy bitcoin in February, if negative return in February, sell the bitcoin March and so on. I have left out the first year of bitcoin as the 2000% increase was unprecedented and unlikely to be repeated. So using our strategy from the 31st August 2011 to 31st August 2013 we recorded a 2775% return on our initial investment of $100, this compares to a return of 810% if a buy and hold strategy were adopted

Limitations & Possible Extensions

The basic nature of our tests may cause some readers concern, especially given the profits available to informed investors if our results were to hold. Therefore extensions may be necessary to confirm our results. The duration analysis carried out by Chou et al 2014, is one such extension. In this study, the price duration of winner and loser stocks are examined. "The duration of a winner is defined as the length of time during which the cumulated return reach the maximum level after formation date; while the duration of a loser is defined as the length of time during which the cumulated return reach the minimum level after formation date. If a stock's price duration is lengthier than the other, we conjecture that such stock persists more". This methodology could perhaps be incorporated into a future study. As I have found evidence of investor overreaction after two periods, the trading strategy used in this analysis could be extended. In the future I would like to devise a more complex trading strategy to incorporate this result. Further examination could also look at the peculiar difference in sign on our Gold and Oil variables when regressed on bitcoin returns and perhaps compare results with analysis on other digital currencies such as litecoin and anoncoin to see if they show any differences.

Conclusion

The results of this study have shown the bitcoin market to be inefficient and suggest there is a possibility to make abnormal returns using historical data. The augmented dickey fuller and runs test found evidence against returns following a random walk, suggesting that they may follow a predictable pattern. We found a statistically significant positive relationship between returns in the current period and the previous period. This suggests that to make excess returns tomorrow an investor should buy if returns are positive today and sell if returns are negative today. This result was confirmed by our momentum dummy variable test which showed a significant positive relationship between returns today and a positive price change yesterday. Interestingly the negative coefficient on returns from two days ago suggests that this momentum in returns only exists for a short period, if investors react too late (i.e. after the first day in our model) they will end up losing money. Finally we demonstrated that using a strategy which accounts for the momentum anomaly will significantly outperform traditional strategies over a random period of bitcoin prices.

It seems clear that bitcoin does not satisfy even the weakest form of EMH. Smart investors should then be able to make abnormal profits on bitcoin by studying the price time series. Further, the significant evidence of momentum in daily returns suggests they should be able to profit by simply buying bitcoin when they witness a price rise. If significant numbers of these smart investors were doing so, prices would be driven to fundamental value (viewed by many to be zero for bitcoin) and the inefficiencies would be eliminated. Our study of behavioural finance may reveal why this has not happened. The huge volatility in bitcoin returns presents a problem for smart investors. If these investors are acting on behalf of a client they face an agency problem. An investor aware of the momentum effect may realise returns are on average higher the day after a price rise, but the volatility in the overall daily returns may make the asset too risky. Another explanation could be that these arbitrageurs take the form positive feedback traders intentionally inflating the price to cash out at the peak. The results from our autoregression and dummy variable test make this unlikely however as returns seem to only show positive serial correlation in the very short term.

In conclusion bitcoin is yet another example of the impracticality of EMH stringencies in an empirical setting. The level of inefficiency within the bitcoin market seems to back up claims it is doomed to crash. However at the time of writing bitcoin has surprised many by coming through the bankruptcy of the MTGOX exchange relatively unscathed. Many expected the fall of one of bitcoins biggest exchanges to cause mass panic but the price did not fall as expected and rebounded this week getting close to a three week high (as of Monday 3rd March). In the long run, it seems implausible for a viable currency to exhibit bitcoins level of volatility, for the time being however it seems to be here to stay.

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