Determinants of Bitcoin Expected Returns

Frederick Adjei

Economics and Finance Department, Southeast Missouri State University, One University Plaza, Cape Girardeau
*Corresponding author: fadjei@semo.edu

Received December 10, 2018; Revised January 12, 2019; Accepted January 22, 2019

Abstract In this study, we investigate the relationship between Bitcoin mining technology variables and Bitcoin returns, using a GARCH-M model. Additionally, we examine the predictive power of the mining technology variables on future Bitcoin returns. We find that mining difficulty and block size are inversely related to Bitcoin returns. Additionally, our findings signify that the higher the block size the lower the Bitcoin price and consequently the lower the expected return. Second, our findings show that mining difficulty and block size are robust predictors of future Bitcoin returns.

Keywords: Bitcoin expected returns

Cite This Article: Frederick Adjei, “Determinants of Bitcoin Expected Returns.” Journal of Finance and Economics, vol. 7, no. 1 (2019): 42-47. doi: 10.12691/jfe-7-1-5.

1. Introduction

Bitcoin has risen in importance as an electronic payment system or pseudo-currency, and also as a speculative asset. Due to the nature and limitations of the mining technology, the market microstructure, and the seemingly irrational investor interest in Bitcoin, expected returns may be determined by non-traditional variables. Particularly, mining technology parameters may be limiting factors in Bitcoin availability and expected returns.

In this study, we investigate the relationship between Bitcoin mining technology variables and Bitcoin returns, specifically, the effects of hash rate, mining difficulty, and block size, on Bitcoin returns, using a GARCH-M model. Additionally, we examine the predictive power of the mining technology variables on future Bitcoin returns.

2. Extant Research on Bitcoin

According to the Satoshi Nakamoto [1] whitepaper, Bitcoin is an electronic payment system that does not depend on trust, and its growth is determined by factors such as incentives to mine new Bitcoins, the ease and integrity of transactions; effected by the hash and hash rate, a verification system; executed by a network of nodes or computers and the peer-to-peer based distributed timestamp server which results in a block chain. Additionally, according to the extant research such as Grinberg [2], Buchholz, Delaney, Warren, and Parker [3], Kristoufek [4], Bouoiyour and Selmi [5], and Balcilar, Bouri, Gupta, and Roubaud [6] find that Bitcoin performance is determined by fundamental, macroeconomic, and speculation factors.

This study adds to the extant literature, by investigating the impact of market microstructure and mining technology on expected returns of Bitcoin. Ciaian, Rajcaniova, and Kancs [7] find that the interaction between demand and supply of Bitcoin impacts performance. Demand is driven by speculation and use of Bitcoin as a Medium of exchange, while supply is determined by the mining velocity Bitcoin. Bouoiyour and Selmi [5] find that macroeconomic and financial indicators are correlated with the use of Bitcoin in the market. Higher economic activity will increase demand for Bitcoin which may increase its price and hence returns. Lee [8] finds that negative news contributes to high Bitcoin prices and Bouoiyour and Selmi [5] document that following the devaluation of the Venezuelan bolivar and the demonetization [500 and 1,000 rupee notes ] in India, the interest in Bitcoin increased significantly in these two countries.

The hash rate, which is the pace at which a computer is executing an operation to build a Bitcoin blockchain, is a gauge of the processing capability of the Bitcoin system. Bouoiyour and Selmi [5] find that the increased demand for processing power in the Bitcoin network will require significant investment in costly computer hardware which in turn will affect the speed of mining and ultimately the price of Bitcoin.

Balcilar, Bouri, Gupta, and Roubaud [6] find that Bitcoin trading volume has a predictive power for future returns, hypothesize that practitioners could construct volume-based strategies to increase their profits, and suggest that this is evidence of weak-form efficiency in the Bitcoin market.

3. Bitcoin Mining Technology Variables and Bitcoin Return

To develop a model of Bitcoin returns, we have to comprehend the theoretical associations between exogenous variables and expected returns of Bitcoin. Most of the exogenous variables discovered by the existing
studies as predictors of expected returns of Bitcoin are mainly indicators of the condition of the economy. For instance, Balciu, Boui, Gupta, and Roubaud [6] document that Bitcoin performance is determined by macroeconomic, fundamental, and speculation factors.

In this study, we examine the power of mining technology variables as determinants of Bitcoin returns and also the predictive power of mining technology variables expected Bitcoin returns. The main Bitcoin mining technology variables used in this study are: hash rate, mining difficulty, and block size.

To maintain transactional anonymity and security, the Bitcoin network must continually make rigorous computations to encrypt and track the mining process and trading transactions. This requirement demands high processing power and is measured by the hash rate. The hash is the result of a mapping function (hash function), and for Bitcoin, the function serves to map non-uniform data to uniform data. The speed of the mapping process is the hash rate. Therefore the higher the hash rate, the quicker the mining of new Bitcoins. With increased Bitcoin supply, ceteris paribus, there should be a decline in Bitcoin price.

Mining difficulty is the computational complexity of processing a hash function to generate an output: a hash, in the mining of Bitcoins. The higher the degree of complexity, the more processing time it takes and hence mining difficulty is inversely related to the hash rate. However, these relationships are moderated by the Bitcoin Network management’s adjustment of the mining difficulty approximately every fortnight with the goal of a mining rate of 12.5 Bitcoins every 10 minutes. We hypothesize that the higher the mining difficulty the higher the Bitcoin price and consequently the higher the expected return.

Transactions conducted in Bitcoin have to be validated by miners and subsequently shared on the public ledger: the blockchain. A block is a collection of transactions that require validation and the size of each block cannot exceed 1MB. According to TradeBlock.com, the mean block size has increased from 125KB to 975KB since 2013, with some blocks reaching the 1MB limit.

A practical consequence of the block size limit is that as more patrons execute trades over the Bitcoin network, the number of transactions in a block will increase, reaching the limit frequently, relegating some transactions to subsequent blocks, and resulting in delays in transaction validation. These delays will make the Bitcoin currency less attractive as a medium of exchange, reducing the price of Bitcoin and consequently future returns. We hypothesize that the higher the block size the lower the Bitcoin price and consequently the lower the expected return. Additionally, naturally, as the number of transactions increase the block size limit will be hit quicker, as discussed earlier, leading to a decline in Bitcoin price and subsequent returns.

4. Using the Garch-M Model

In this study, we hypothesize that mining technology determines Bitcoin returns and examine the effects of the following mining technology variables; hash rate, mining difficulty, block size, and number of transactions, on Bitcoin returns. To test our hypothesis, we use the GARCH-M model, control for business cycle variations, and examine the contemporaneous effects of mining technology variables on the conditional mean of Bitcoin returns.

To control for business cycle variations, we use Bitcoin returns minus market returns (using S&P 500 Index returns) as the dependent variable in our model. Additionally, we control for other blockchain technology effects by including blockchain control variables; hourly volatility, and number of transactions.

In the conditional mean and conditional risk literature, time-varying risk has traditionally been modeled using GARCH models. The basic concept in a GARCH-M model is to incorporate the conditional variance of returns; \( h_t \), in the conditional mean equation and examine the effect of the conditional variance on the conditional mean of Bitcoin return minus market returns (using S&P 500 Index returns); \( r_t \).

This is formally stated as

\[
 r_t = \psi + \delta h_t + h_t^{1/2} \varepsilon_t, \tag{1}
\]

where \( \varepsilon_t \sim IID (0, 1) \). Extant research assumes the conditional variance follows the GARCH (1,1) model

\[
 h_t = \omega + \beta h_{t-1} + \alpha \varepsilon_{t-1}^2, \tag{2}
\]

where \( u_t = r_t - \psi - \delta h_t \) and \( \omega > 0, \beta \geq 0, \) and \( \alpha > 0 \).

In this study, we extend the GARCH-M model by incorporating exogenous variables (as in [9]); mining technology variables; hash rate, mining difficulty, and block size, and control variables: number of transactions; into the conditional mean and conditional variance equations of GARCH-M setup as follows:

\[
 r_t = \psi + \Phi X_t + \delta h_t + h_t^{1/2} \varepsilon_t, \tag{3}
\]

where \( \psi \) is the intercept term, \( \varepsilon_t \sim IID (0, 1) \), \( \Phi \) is a matrix of slope coefficients, \( X_t \) is a vector of mining technology variables; natural log of hash rate, mining difficulty, and natural log of block size, as well as blockchain control variables natural log of trades per minute, time between trades, hourly volatility, natural log of number of transactions;

\[
 h_t = \omega + \beta h_{t-1} + \alpha u_{t-1}^2, \tag{4}
\]

where \( u_t = r_t - \psi - \delta h_t \) and \( \omega > 0, \beta \geq 0, \) and \( \alpha > 0 \).

Following Nyberg [9], we estimate our GARCH-M models using maximum likelihood and assuming the error term follows the Student’s \( t \) distribution.

5. Data and Descriptive Statistics

Daily price and mining technology data from July 17, 2010 to February 28, 2018 is obtained from Bitcoingity.org website. Descriptive statistics of the main variables used in the study are presented in Table 1. The mean price of Bitcoin during the sample period is $967.81 with a minimum of $0.050 and a maximum of $19454.36. The mean daily return is 0.7%, with a minimum of -39.6% and a maximum of 57.5%. The quoted price standard deviation is the dispersion among quoted prices from eight Bitcoin
trading exchanges: BTC, CEX, Coinbase, Coinsetter, Gemini, LakeBTC, MtGox, and OKCoin. The mean quoted price standard deviation is $19.90 with a minimum of $0 and a maximum of $752. The mean number of daily transactions is 108472 with a minimum of 260 transactions and maximum of 490644 transactions a day.

Table 2 displays the results of the GARCH-M model with daily and monthly data. Columns 1 and 3 show the original GARCH-M model for daily and monthly returns respectively, run with no exogenous variables: mining technology variables and presents evidence of the presence of GARCH effects (model 1 shows that the coefficients are statistically significant at the 1% level).

Columns 2 and 4 show the original GARCH-M model for daily and monthly returns respectively run with exogenous variables: mining technology variables. Controlling for business cycle effects, we find that the coefficient for hash rate is positive and statistically significant at the 1% level, indicating a direct relationship between hash rate and Bitcoin returns. Additionally, mining difficulty and block size coefficients are negative and statistically significant at the 1% level, indicating an inverse relationship between these variables and Bitcoin returns for the daily data. However, with monthly data, there is less statistical power due to the number of observations and hence the results are not significant.

### Table 1. Descriptive Statistics

#### Panel A: Market

| Variable          | Mean     | Median    | Min.    | Max.     | Std. Dev. |
|-------------------|----------|-----------|---------|----------|-----------|
| Mean Price        | 967.812  | 252.944   | 0.050   | 19454.36 | 2486.21   |
| Daily Return      | 0.007    | 0.003     | -0.596  | 0.575    | 0.051     |
| Quoted Price STD  | 19.895   | 2.643     | 0       | 752.070  | 76.561    |
| Trades Per Minute | 29.576   | 17.814    | 0       | 396.920  | 40.774    |
| Hourly Volatility | 5.133    | 0.579     | 0.000   | 282.142  | 16.566    |
| Trading Volume    | 1.28 x 10^8 | 6.24 x 10^6 | 0 | 6.44 x 10^9 | 4.17 x 10^9 |
| LN(Trading Volume)| 15.032   | 36.192    | 21.156  | 43.660   | 5.167     |
| SP500 Daily Return| 0.0005   | 0.0005    | -0.0666 | 0.0474   | 0.0090    |

#### Panel B: Blockchain

| Variable                  | Mean       | Median     | Min.     | Max.      | Std. Dev. |
|---------------------------|------------|------------|----------|-----------|-----------|
| Hash Rate                 | 2.78 x 10^7 | 5.23 x 10^7 | 1.54 x 10^8 | 9.15 x 10^8 | 1.05 x 10^8 |
| LN(Hash Rate)             | 34.109     | 36.192     | 21.156   | 43.660    | 5.167     |
| Mining Difficulty         | 1.99 x 10^11 | 8.00 x 10^8 | 181.543  | 3.01 x 10^12 | 4.66 x 10^11 |
| LN(Mining Difficulty)     | 20.191     | 22.803     | 5.203    | 28.733    | 6.324     |
| Number of Transactions    | 108472.8   | 66902.5    | 260      | 490644    | 103721.3  |
| LN(Number of Transactions)| 10.707     | 11.111     | 5.561    | 13.104    | 1.796     |
| Time Between Blocks       | 9.262      | 9.284      | 4.685    | 18.758    | 1.362     |
| Block size (kilobytes)    | 309.590    | 156.840    | 0.215    | 998.175   | 347.055   |
| LN(Block size)            | 11.831     | 12.325     | 6.001    | 13.814    | 1.987     |

### Table 2. Estimation results of GARCH-M models

| Variable                 | GARCH-M without VAR (daily) | GARCH-M with VAR (daily) | GARCH-M without VAR (monthly) | GARCH-M with VAR (monthly) |
|--------------------------|-----------------------------|--------------------------|-----------------------------|--------------------------|
| Intercept                | 0.0016 (0.011)              | -0.0368 (0.0203)         | 0.0660 (0.0520)             | -0.5726 (0.3917)         |
| ARCH0                    | 0.0001 (0.000)              | 0.0001 (0.000)           | 3.0583 (0.9675)             | 0.3167 (0.9184)          |
| ARCH1                    | 0.4095 (0.000)              | 0.4379 (0.000)           | 17.0743 (0.9674)            | 2.1001 (0.9182)          |
| GARCH1                   | 0.6817 (0.000)              | 0.6732 (0.000)           | 0.0000 (0.000)              | 0.5746 (0.0089)          |
| DELTA                    | 1.0324 (0.000)              | 0.8159 (0.0228)          | -0.0005 (0.9690)            | -0.0059 (0.9255)         |
| TDFI                     | 0.2854 (0.005)              | 0.3000 (0.000)           | 0.4952 (0.000)              | 0.4896 (0.000)           |
| Log Likelihood           | 3722.9866                   | 3748.502                 | -41.6369                    | -28.571                  |
| N                        | 1917                        | 1917                     | 90                          | 90                       |

NOTE: Significance of TDFI parameter from zero indicates differences in ML estimates under the assumption of normality and under the assumption of the t-distribution
6. Bitcoin Return Predictability

As a robustness check, we examine the predictive power of the mining technology variables for future returns of Bitcoin by employing the multiperiod forecasting model of Fama and French [10];

$$\sum_{n=1}^{N} r_{t+N} = a + bX_t + u_{t+N}$$

where \( r_{t+N} \) is the daily (monthly) continuously compounded excess return, with the excess return computed as the daily (monthly) and daily (monthly) return on Bitcoin minus the daily (monthly) return on S&P500 index, \( X_t \) is a 1 x \( m \) matrix of \( m \) mining technology variables; hash rate, mining difficulty, block size, and number of transactions; \( b \) is a 1 x \( m \) matrix of slope coefficients, \( N \) is the forecasting horizon in months, and \( u_{t+N} \) is the regression residual. We estimate daily (monthly) regressions for different time horizons: \( N = 2, 5, 20, 60, \) and 120 days [3, 6, 12, 18, and 24 months].

We address the issues presented by overlapping observations in regressions, such as serial correlation and conditional heteroskedasticity in regression residuals, and correlated slopes invalidating inferences from any one regression. We employ the Richardson and Stock [11] joint slopes test which is predicated on the average of the regression beta coefficients. Additionally, we employ a GMM estimator. Using the GMM estimator solves the serial correlation and conditional heteroskedasticity problems [12]. The GMM estimator \( \theta = (a, b) \) with an asymptotic distribution of \( \sqrt{T}(\theta - \theta) \sim N(0, \Omega) \), with \( \Omega = \Sigma_{0}^{-1} \Sigma_{0} \Sigma_{0}^{-1}, \Sigma_{0} = E(x_t x_t'), \) and \( x_t = \delta X_t \), where \( S_0 \) is the spectral density computed at frequency zero of \( w_{t+N} = u_{t+N} x_t \).

Under the null hypothesis that expected returns of Bitcoins are not predictable,

$$S_0 = \sum_{j=N}^{N-1} E(w_{t+N} w_{t+N-j}'),$$

with \( S_0 \) computed with the Newey-West correction with \( N-1 \) moving average lags. The resultant statistic from the analysis is the asymptotic \( Z \) statistic.

As an extension of the Richardson and Stock [11] joint slopes test, we compute the GMM estimator using a system of numerous equations in which the coefficients are restricted to be the same across equations converting the GMM estimator into a special case of the single-equation GMM estimation [see Hayashi]. We proceed as follows for regressions on daily data;

$$\sum_{t=1}^{t=2} r_{t+2} = a + b_2 x_{t+2} + u_{t+2}$$

$$\sum_{t=1}^{t=5} r_{t+5} = a + b_5 x_{t+5} + u_{t+5}$$

$$\sum_{t=1}^{t=20} r_{t+20} = a + b_{20} x_{t+20} + u_{t+20}$$

with \( b = b_2 = b_5 = b_{20} = b_{50} = b_{120} \) and all variables previously defined with \( t \) being the forecasting horizon in days. Obviously, \( S_0 \) cannot be estimated with the Newey-West correction (\( N-1 \) moving average lags cannot be applied) in this case.

For monthly data regressions, we proceed as follows;

$$\sum_{t=1}^{t=3} r_{t+3} = a + b_3 x_{t+3}$$

$$\sum_{t=1}^{t=6} r_{t+6} = a + b_6 x_{t+6}$$

$$\sum_{t=1}^{t=12} r_{t+12} = a + b_{12} x_{t+12}$$

$$\sum_{t=1}^{t=18} r_{t+18} = a + b_{18} x_{t+18}$$

$$\sum_{t=1}^{t=24} r_{t+24} = a + b_{24} x_{t+24},$$

with \( b = b_3 = b_6 = b_{12} = b_{18} = b_{24} \) and all variables previously defined with \( t \) being the forecasting horizon in months.

6.1. Bitcoin Return Predictability Results

In this section, we discuss the results of our predictability regressions. We present the results for daily data in Table 3. Consistent with our Garch-M results, from the 5-day to the 120-day horizon, hash rate, mining difficulty, and block size have predictive power for future Bitcoin returns. As the prediction horizon increases, the adjusted \( R^2 \) increases. The increase in size of adjusted \( R^2 \) with increase in prediction horizon may be due to the persistence of the regressors, as suggested by Cochrane [13]. Hence, we examine the hash rate, mining difficulty, and block size with the joint slopes test; employing the GMM estimator. Consistent with our earlier results, joint slopes for hash rate, mining difficulty, and block size are significantly different from zero at the 1% level.

Results for monthly data are presented in Table 4. From the 3-month to the 24-month horizon, only block size has predictive power for future Bitcoin returns. As with the daily data, with the monthly data, we examine the hash rate, mining difficulty, and block size with the joint slopes test; using the GMM estimator. Joint slopes for mining difficulty and block size are significantly different from zero at the 1% level.

The results altogether show that hash rate, mining difficulty, and block size have forecasting power for future Bitcoin returns. The findings present strong evidence that Bitcoin mining technology variables; hash rate, mining difficulty, and block size, are useful predictors of future returns.
future difficulty and block size.

Future studies could examine the effect of economic policy uncertainty or political uncertainty on the demand for Bitcoin as well as Bitcoin returns in other countries.

7. Conclusion

In this study, we investigate the relationship between Bitcoin mining technology variables and Bitcoin returns, specifically, the effects of mining difficulty and block size, on Bitcoin returns, using a GARCH-M model. Additionally, we examine the predictive power of the mining technology variables on future Bitcoin returns.

First, the findings of the GARCH-M estimation indicate that mining difficulty and block size have an impact on Bitcoin returns with mining difficulty and block size negatively related with Bitcoin returns. Additionally, our findings on block size are consistent with our hypothesis signifying that the higher the block size the lower the Bitcoin price and consequently the lower the expected return. Second, our findings show that mining difficulty and block size are robust predictors of future Bitcoin returns. Particularly, our results present the first unambiguous evidence of a relationship between Bitcoin mining technology variables and Bitcoin returns. Future studies could examine the effect of economic policy uncertainty or political uncertainty on the

References

[1] Satoshi Nakamoto. (2008). Bitcoin: A Peer-to-Peer Electronic Cash System - Bitcoin.org, the bitcoin white paper.
[2] Grinberg, Reuben. “Bitcoin: An Innovative Alternative Digital Currency.” Hastings Science & Technology Law Journal 4 (2011): 160-210.
[3] Buchholz, Martis , Jess Delaney, Joseph Warren and Jeff Parker. “Bits and Bets Information, Price Volatility, and Demand for BitCoin”. Working paper.
[4] Kristoufek, Ladislav. “Quantifying the relationship between phenomena of the Internet and the demand for Bitcoin.” Information Systems and E-Business Management, 14 (2016), Issue 4: 883-919.
[5] Balcilar, Mehmet, Elie Bouri, Rangan Gupta, and David Roubaud. “What Does Bitcoin Look Like?” Annals of Economics and Finance, 16 (2015), issue 2: 449-492.
[6] Ciaian, Pavel , Mirosława Rajcaniova, and d’Artis Kancs. “The Economics of Bitcoin Price Formation.” Information Systems and E-Business Management, 14 (2016), Issue 4: 883-919.
Lee, T.B. “These four charts suggest that BitCoin will stabilize in the future.” Washington Post (2014), http://www.washingtonpost.com/blogs/the-switch/wp/2014/02/03/thesefour-charts-suggest-that-bitcoin-will-stabilize-in-the-future/

Nyberg, Henri. “Risk–return tradeoff in U.S. stock returns over the business cycle.” Journal of Financial and Quantitative Analysis 47 (2012): 137-158.

Fama, Eugene F, and Kenneth R. French. “Business conditions and expected returns on stocks and bonds.” Journal Financial Economics 25 (1989): 23-49.

Richardson, Matthew, and James H. Stock. “Drawing inferences from statistics based on multiyear asset returns.” Journal of Financial Economics 25 (1989): 323-348.

Hansen, Lars Peter. “Large Sample Properties of Generalized Method of Moments Estimators,” Econometrica 50.4 (1982): 1029-1054.

Cochrane, John H. “The dog that did not bark: A defense of return predictability.” Review of Financial Studies 21.4 (2008): 1533-1575.

© The Author(s) 2019. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (http://creativecommons.org/licenses/by/4.0/).