Journal of Finance and Economics, 2019, Vol. 7, No. 1, 42-47
Available online at http://pubs.sciepub.com/jfe/7/1/5
Published by Science and Education Publishing
DOI:10.12691/jfe-7-1-5

Determinants of *Bitcoin* Expected Returns

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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 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.

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 *Bitcoin*s, 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 time 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, Balcilar, Bouri, 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 *Bitcoin*s. 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 *Bitcoin*s. 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 *Bitcoin*s 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 ε_t – IID (0, 1). Extant research assumes the conditional variance follows the GARCH (1,1) model

$$h_t = \omega + \beta h_{t-1} + \alpha u^2_{t-1}, \tag{2}$$

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:

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

where ψ is the intercept term, ε_t – IID (0, 1), Φ is a matrix of slope coefficients, $\boldsymbol{X_t}$ 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*;

$$h_t = \omega + \beta h_{t-1} + \alpha u^2_{t-1}, \tag{4}$$

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 *Bitcoin*ity. 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 impregnation: 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

	Mean	Median	Min.	Max.	Std. Dev.
Panel A: Market					
Mean Price	967.812	252.944	0.050	19454.36	2486.21
Daily Return	0.007	0.003	-0.396	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	1.28×10^{8}	6.44×10^{6}	5	6.25×10^{9}	4.17×10^{8}
LN(Trading Volume)	15.032	36.1923	21.156	43.660	5.167
SP500 Daily Return	0.0005	0.0005	-0.0666	0.0474	0.0090
Panel B: Blockchain					
	Mean	Median	Min.	Max.	Std. Dev.
Hash Rate	2.78×10^{17}	5.23×10^{15}	1.54×10^{9}	9.15×10^{18}	1.05×10^{18}
LN(Hash Rate)	34.109	36.192	21.156	43.660	5.167
Mining Difficulty	1.99×10^{11}	8.00×10^{9}	181.543	3.01×10^{12}	4.66×10^{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)
Φ				
LN(Block Size)		-0.0090 (0.0031)		-0.3026 (0.0569)
LN(Hash Rate)		0.0008 (0.1437)		-0.0001 (0.9976)
LN(Mining Difficulty)		-0.0021(0.000)		-0.0369 (0.0839)
LN(Number of Transactions)		0.0149 (0.000)		0.4626 (0.0035)
Volatility		0.0001 (0.0531)		0.0065 (0.0098)
Intercept	0.0016 (0.011)	-0.0368 (0.0023)	0.0600 (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)	0.000(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)	0.300 (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];

$$\sum_{n=1}^{N} \frac{r_{t+N}}{N} = a + b\text{x}X_t + u_{t+N,t} \quad (5)$$

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, $\boldsymbol{X}_t$ is a 1 x *m* matrix of *m* mining technology variables; hash rate, mining difficulty, block size, and number of transactions; $\boldsymbol{b}$ is a 1 x *m* matrix of slope coefficients, N is the forecasting horizon in months, and $u_{t+N,t}$ 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 θ = (a, $\boldsymbol{b}$) with an asymptotic distribution of $\sqrt{T}(\hat{\theta} - \theta) \sim N\,(0,\ \Omega)$, with Ω = $Z_0^{-1} S_0 Z_0^{-1}$, $Z_0 = E(x_t x_t^{'})$, and $x_t = (1\ X_t^{'})^{'}$, where S_0 is the spectral density computed at frequency zero of w_{t+N} = $u_{t+N,t}\, x_t$.

Under the null hypothesis that expected returns of *Bitcoin*s are not predictable,

$$S_0 = \sum_{j=-N+1}^{N-1} E\left(w_{t+N} w'_{t+N-j}\right), \quad (6)$$

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;

$$\sum_{t=1}^{t=2} \frac{r_{t+2}}{2} = a + b_2\text{x}X_t + u_{t+2,t} \quad (7)$$

$$\sum_{t=1}^{t=5} \frac{r_{t+5}}{5} = a + b_5\text{x}X_t + u_{t+5,t} \quad (8)$$

$$\sum_{t=1}^{t=20} \frac{r_{t+20}}{20} = a + b_{20}\text{x}X_t + u_{t+20,t} \quad (9)$$

$$\sum_{t=1}^{t=60} \frac{r_{t+60}}{60} = a + b_{60}\text{x}X_t + u_{t+60,t} \quad (10)$$

$$\sum_{t=1}^{t=120} \frac{r_{t+120}}{120} = a + b_{120}\text{x}X_t + u_{t+120,t}, \quad (11)$$

with $b = b_2 = b_5 = b_{20} = b_{60} = b_{120}$ 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;

$$\sum_{t=1}^{t=3} \frac{r_{t+3}}{3} = a + b_3\text{x}X_t + u_{t+3,t} \quad (12)$$

$$\sum_{t=1}^{t=6} \frac{r_{t+6}}{6} = a + b_6\text{x}X_t + u_{t+6,t} \quad (13)$$

$$\sum_{t=1}^{t=12} \frac{r_{t+12}}{12} = a + b_{12}\text{x}X_t + u_{t+12,t} \quad (14)$$

$$\sum_{t=1}^{t=18} \frac{r_{t+18}}{18} = a + b_{18}\text{x}X_t + u_{t+18,t} \quad (15)$$

$$\sum_{t=1}^{t=24} \frac{r_{t+24}}{24} = a + b_{24}\text{x}X_t + u_{t+24,t}, \quad (16)$$

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.

Table 3. Multivariate Forecasting Regressions with Daily Data

Horizons	*2days*	*5days*	*20days*	*60days*	*120days*	*Joint Slopes Coefficient*
Variable	*β* (*p-value*)	*β* (*p-value*)	*β* (*p-value*)	*β* (*p-value*)	*β* (*p-value*)	*Z(B)* (*p-value*)
Intercept	-0.0155 (0.4603)	-0.0101 (0.4878)	-0.0072 (0.3771)	0.0006 (9196)	0.0307 (0.000)	0.0244 (0.000)
LN(Block Size)	-0.0099 (0.0404)	-0.0141 (0.000)	-0.0135 (0.001)	-0.0117 (0.000)	-0.0081 (0.000)	-0.0074 (0.000)
LN(Hash Rate)	0.0007 (0.4589)	0.0007 (0.2877)	0.0007 (0.0593)	0.0008 (0.0032)	-0.0004 (0.0307)	-0.0003 (0.0254)
LN(Mining Difficulty)	-0.0022 (0.0180)	-0.0020 (0.0021)	-0.0019 (0.000)	-0.0014 (0.000)	-0.0001 (0.4197)	-0.0004 (0.0007)
LN(Number of Transactions)	0.0146 (0.0052)	0.0184 (0.000)	0.0172 (0.000)	0.0135 (0.000)	0.0081 (0.000)	0.0082 (0.000)
Volatility	0.0001 (0.2798)	0.0001 (0.1301)	0.0001 (0.008)	-0.0001 (0.0026)	-0.0000 (0.0384)	0.0000 (0.2735)
Adj. R^2	0.0130	0.0336	0.100	0.1555	0.2948	GMM 157.7 (0.000)
N	1917	1917	1917	1917	1917	1917

Table 4. Multivariate Forecasting Regressions with Monthly Data

Horizons	*3 months*	*6 months*	*12 months*	*18 months*	*24 months*	*Joint Slope Coefficient*
Variable	*β* (*p-value*)	*β* (*p-value*)	*β* (*p-value*)	*β* (*p-value*)	*β* (*p-value*)	*Z(B)* (*p-value*)
Intercept	0.5221 (0.3387)	0.9313 (0.0119)	0.5739 (0.0290)	0.4239 (0.0600)	0.5400 (0.0080)	0.5648 (0.000)
LN(Block Size)	-0.6130 (0.0002)	-0.3999 (0.0002)	-0.1851 (0.0150)	-0.0896 (0.1660)	-0.0982 (0.0907)	-0.2548 (0.000)
LN(Hash Rate)	-0.0083 (0.7481)	-0.0266 (01243)	-0.0243 (0.0506)	-0.0178 (0.0948)	-0.0175 (0.0666)	-0.0170 (0.001)
LN(Mining Difficulty)	-0.0133 (0.5640)	0.0084 (0.5871)	0.0015 (0.8916)	0.0031 (0.7404)	0.0126 (0.1389)	0.0023 (0.5993)
LN(Number of Transactions)	0.6900 (0.000)	0.4338 (0.000)	0.2345 (0.0044)	0.1194 (0.0871)	0.0997 (0.1101	0.2890 (0.000)
Volatility	0.0019 (0.4763)	0.0017 (0.3394)	0.0016 (0.2129)	0.0009 (0.4125)	0.0004 (0.666)	0.0010 (0.0821)
Adj. R^2	0.2441	0.3145	0.2719	0.1244	0.0743	GMM75.54 (0.0004)
N	90	90	90	90	90	90

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 demand for *Bitcoin* as well as *Bitcoin* returns in other countries.

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