PREDICTING BITCOIN RETURN AND VOLATILITY USING GOLD AND THE STOCK MARKET

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ABSTRACT

There is significant interest in the growth and development of cryptocurrencies, the most notable being Bitcoin. Interest in such currencies is global, the price movements is said to be highly speculative and "bubble-like". Since these cryptocurrencies trade like stocks, provide alternative to gold, and appreciate during uncertain times, it can be hypothesized that their prices are partly determined by the stock index, gold prices, and the fear gauge (VIX). In this paper, we test this hypothesis by conducting time-series analysis of the returns and volatilities of Bitcoin price, Stock market (S&P 500 index), and gold price. We use the Autoregressive-moving-average model with exogenous inputs model (ARMAX), Generalized Autoregressive conditionally heteroscedastic (GARCH) model, Vector autoregression (VAR) model, and Granger causality tests to determine linkages between the S&P500, gold, Bitcoin prices, and their respective returns, and volatilities. We find that Bitcoin's volatility (a proxy for risk) is easier to forecast compared to the return, physical gold returns can influence Bitcoin returns, and Bitcoin is an uncorrelated asset class to stocks and gold.

JEL classification: G11, G17

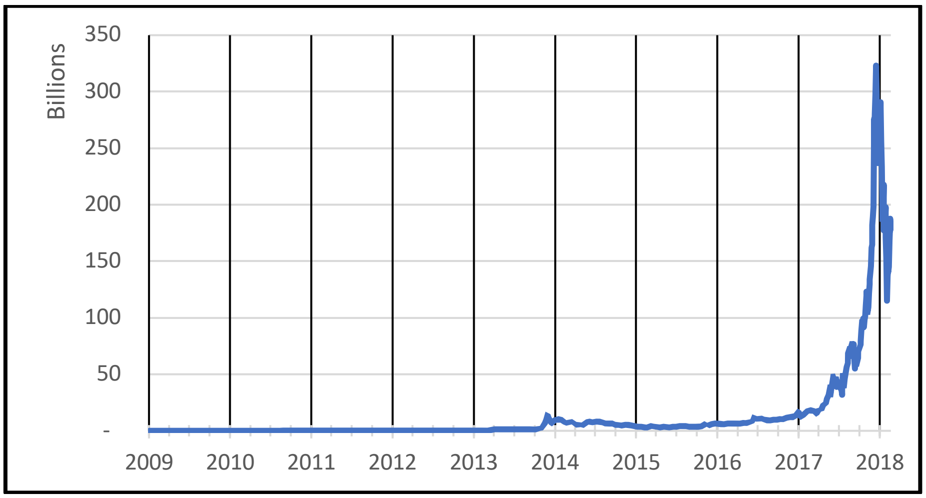
Keywords: asset management; alternative investments; digital currency; crypto currency; bitcoin

INTRODUCTION

Bitcoin is a consensus network that enables a new payment system and is considered a completely "digital currency." It is the first decentralized peer-to-peer payment network that is powered by its users with no central authority or middlemen (bitcoin.org [2019]). Bitcoin has had an astounding rise in popularity in recent times. Many believe that it is the currency of the future, and the rise in its price has been attributed to its limited supply. Nakamoto (2008) is said to be the pioneer behind this cryptocurrency. New transactions are announced on a computer network by Bitcoin users connected via internet, and these transactions are verified by network nodes. The transactions are then recorded in a public distributed ledger called the Blockchain. Bitcoins are awarded to miners or users who offer their computing power to verify and record transactions into the blockchain.

As of February 2018, more than 100 million transactions from 23 million digital wallets based in 140 countries are processed by the Blockchain (blockchain.com [2018]). As shown in Figure (1), since Bitcoin's introduction in 2009, the Bitcoin market capitalization grew rapidly from less than a billion USD in 2013 to more than $323 billion in December 2017, after contracting to $177 billion in February 2018 (coinmarketcap.com [2018]). Blockchain transactions have increased from a negligible amount in the year 2010 to $3 Billion USD in February 2018 (blockchain.info [2018]). Bitcoins are exchangeable into other currencies, products, and services. Bitcoin has the largest market capitalization among all cryptocurrencies, but its market capitalization is still a small fraction of all other currencies in circulation. As an example, more than $1.6 Trillion USD are in circulation at the end of 2017 (FRED [2018]).

Figure 1. Market capitalization of Bitcoin in billion $USD



Many studies have been conducted on the volatility of Bitcoin and have concluded that Bitcoin prices tend to be more volatile than those of standard, non-crypto currencies. In this study, we investigate if equity prices or gold prices influence Bitcoin prices (considered by some as digital gold). Specifically, we want to investigate the linkages between the S&P500 index, gold, Bitcoin prices, and their respective returns and volatilities. The relationship between volatility, a measure of fear and uncertainty in the economy, and Bitcoin prices is of particular interest in this study.

We find that Bitcoin volatility can be modeled accurately using the GARCH model, gold returns explain Bitcoin returns, and Bitcoin is an uncorrelated asset to stocks and gold. Our models developed in this paper forecast the direction of returns accurately but miss the magnitude. However, our models forecast the direction as well as the magnitude of volatility accurately.

In section 2, we conduct a Bitcoin literature overview. Section 3 explains description of data and methodology used in this study. Results are discussed in Section 4. Section 5 contains conclusions and directions for future research.

LITERATURE ON THE FACTORS INFLUENCING BITCOIN RETURNS AND VOLATILITIES

Recently, many studies have been conducted to understand the factors influencing Bitcoin returns and volatilities. Financial asset return predictability is of great interest in the financial literature as summarized by Golez and Koudijs (2016). Empirical evidence suggests that stock returns are indeed partially predictable (Campbell and Shiller 1988; Fama and French 1988; Cochrane, 2008; Binsbergen and Koijen 2010). With the advent of Bitcoin, researchers have extended the investment asset universe by adding Bitcoin. For an introduction to the role of money and artificial currencies, see Noga (2018).

Factors Influencing Bitcoin returns

There are few studies on Bitcoin prices, and how those prices move. The most recent study on Bitcoin prices was conducted by Cheah et al (2018). They model cross-market Bitcoin prices as long-memory processes and dynamic inter-dependence in a fractionally cointegrated VAR framework. Their findings suggest that there is long-memory in both individual market and five-market systems indicating non-homogeneous informational inefficiency and a cointegration relationship with slow adjustment of shocks.

Other studies, namely Cheah and Fry (2015) and Katsiampa (2017) report that the recent volatility in Bitcoin prices is an outcome of market sentiments, where the latter can be associated with significant "memory." According to those studies, the "memory" of shocks of Bitcoin prices are semi-important determinants of Bitcoin prices. Dyhrberg (2016a) found that Bitcoin can be an ideal tool for risk-averse investors as a buffer against negative shocks to the market, whereas Dyhrberg (2016b) found that Bitcoin can serve as a hedge against market specific risk.

Van Wijk (2013) found that most of the Bitcoin price influencing variables are related to the U.S. economy. Using daily and weekly data within a DCC model (Engle, 2002), Bouri, et al (2017) showed that Bitcoin can serve as an effective diversifier for most of the cases. Ciaian, et al (2016) found that market forces of Bitcoin supply and demand, arrival of additional information (trust), and speculators are three key drivers of Bitcoin prices. In addition, they did not support previous findings that the global macro-financial development might be driving Bitcoin price.
In this paper, we extend the existing literature by adding the influence of fear and uncertainty in the markets, as measured by the VIX index and physical gold spot prices on Bitcoin prices.

Factors Influencing Bitcoin volatilities

Using the GARCH analysis, Dyhrberg (2016a) found that Bitcoin can combine some of the advantages of both commodities and currencies. Guo and Fantulin (2018) investigate the volatility of Bitcoin and try to predict short-term prices using volatility and trade order book data. Catania et al (2018) tried to predict the conditional volatility of four major cryptocurrencies (Bitcoin, Ripple, Ethereum, and Litecoin). Estrada (2017) found that there exists a bidirectional Granger-causality relationship between Bitcoin realized volatility and the VIX at the 5% significance level.

We take this approach further by incorporating VIX, gold realized volatility (GVOL), and Bitcoin realized volatility (BVOL) as computed by BitMEX (BitMEX [2018]). Kambouroudis and McMillan (2016) found that adding exogenous variables to forecast volatility improves forecast power. We contend that Bitcoin volatility is both exogenous and endogenous. Reason for this belief is that Bitcoin is an artificially derived product created through a computer intensive process. Investors believe that supply of Bitcoins is limited to 21 million out of which 16.8 million are mined as of 01/2018 (Redman [2018]). Since the supply of Bitcoins is potentially fixed, the entire price movement is primarily determined by the demand. Since Bitcoin is considered a 'digital gold', BVOL contains exogenous factors (that can be explained by GVOL) and endogenous (i.e. Bitcoin's demand-side unsystematic risk).

DATA AND METHODOLOGY

Data

We collected daily data on Bitcoin prices in USD from Coindesk (coindesk.com [2018]), VIX closing prices from CBOE (Cboe [2018]), and Gold prices in USD from World Gold Council (GOLDHUB [2018]). The window of analysis is from July 19, 2010 (earliest Bitcoin price available on Coindesk) to February 16, 2018 (most recent). We captured the VIX jump that occurred between February 6th and 12th, 2018. We could have used other alternative digital currencies (such as Ripple, Ethereum, and Litecoin), but decided against it deliberately for two reasons; a) to have a wider data window since some of these digital currencies were released after 2015; and b) others are less significant (i.e. Bitcoin market cap is greater than that of the next 100 combined).

Methodology

Bitcoin prices are available on all seven days of the week. However, gold prices and VIX data are available on US working days. So, VIX dates (from CBOE trading days) are used as a baseline and data for other dates are removed from the dataset. As a result, we have 1,911 observations of prices between 7/19/2010 and 2/16/2018. Daily returns are computed using ln (P_1/P_0) formula where P_1 is today's closing price and P_0 is previous trading day's closing price. Bitcoin volatility is computed using the annualized realized volatility approach of the BitMex (BitMEX [2018]). We computed the 30-day historical volatility index (referred to as the BVOL Index). The Index is a rolling 30 day annualized (365-day) volatility of the daily (11:30 UTC to 12:00 UTC) Time Weighted Average Price (TWAP) of Bitcoin in USD. To be consistent in the implied volatility computations, we used the same BVOL approach to compute gold volatility (GVOL). Due to 30-day rolling average calculations, the sample size of volatilities is 1,884. Summary statistics and historical overview of Bitcoin, Gold, and S&P500 returns and volatilities are provided below in Figures (2) and (3), and Tables (1) and (2). Bitcoin returns are very volatile compared to those of gold and stock market. In addition, BVOL jumps do not coincide with those of GVOL and VIX.

Table 1. Summary Statistics of Bitcoin, Gold, and S&P500 returns and volatilities from 07/19/2010 to 02/16/2018

	BITCOIN_R	GOLD_R	SP500_R	BVOL	GVOL	VIX
Mean	0.64%	0.01%	0.05%	105.39%	18.87%	16.48
Median	0.22%	0.00%	0.06%	91.15%	17.15%	15.10
Maximum	49.97%	4.84%	4.63%	320.16%	46.98%	48.00
Minimum	-44.38%	-9.60%	-6.90%	0.00%	6.98%	9.14
Std. Dev.	6.57%	1.05%	0.90%	64.49%	6.87%	5.62
Skewness	0.14	(0.56)	(0.57)	1.12	1.42	1.92
Kurtosis	11.22	9.62	8.43	3.81	5.13	7.75
Jarque-Bera	5,305	3,539	2,416	446	985	2,929
Observations	1884	1884	1884	1884	1884	1884

Table 2: Correlogram of Bitcoin, Gold, and S&P500 returns and volatilities from 07/19/2010 to 02/16/2018

	BITCOIN_R	GOLD_R	SP500_R
BITCOIN_R	1	0.05	0.06
GOLD_R	0.05	1	-0.02
SP500_R	0.06	-0.02	1

	BVOL	GVOL	VIX
BVOL	1	0.34	0.29
GVOL	0.34	1	0.45
VIX	0.29	0.45	1

Figure 2. Historical returns of Bitcoin, Gold, and S&P500 from 07/19/2010 to 02/16/2018

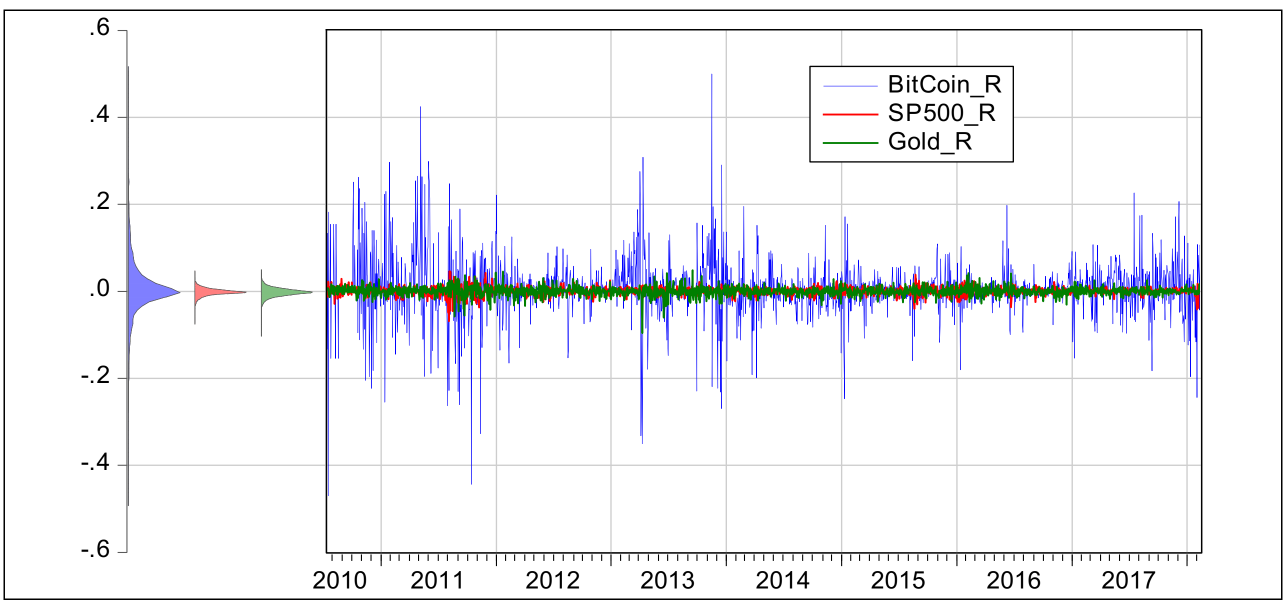
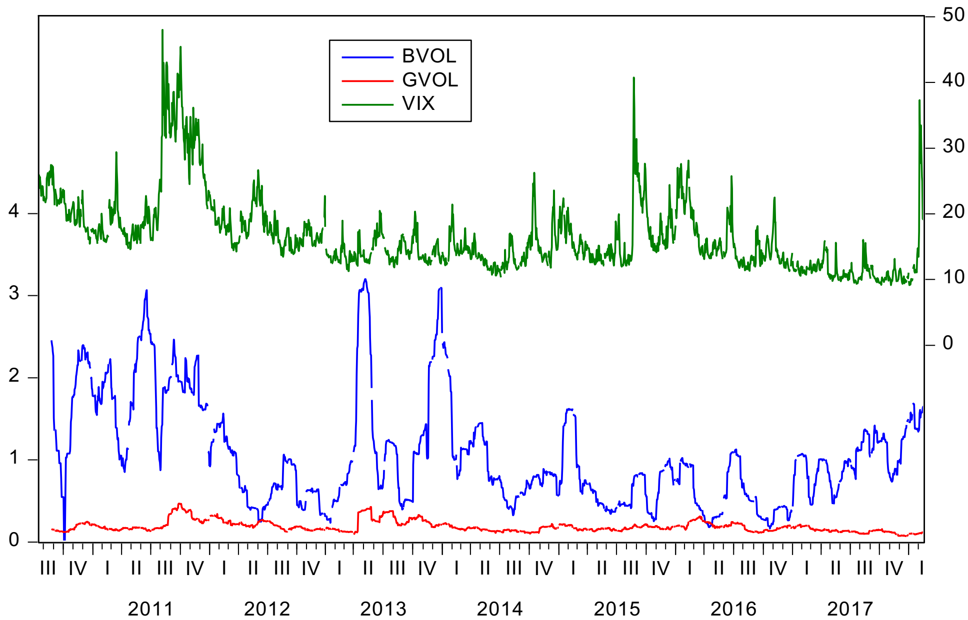


Figure 3. Historical volatility of Bitcoin, Gold, and S&P500 from 07/19/2010 to 02/16/2018.
(BVOL and GVOL on the left axis and VIX on the right axis)



First, we use a basic multiple regression to determine if Bitcoin daily returns can be explained by the daily returns of the S&P500 and gold using Equation (1). We then test for serial correlation in Bitcoin returns and use the ARMAX (p, q, b) model from Baillie (1980) to explain Bitcoin returns using Equation (2), where p is autoregressive term, q is moving average term and b is exogenous inputs term.

$$Bitcoin\_R_t = C_t + SP500\_R_t + Gold\_R_t \qquad \text{- Eq. (1)}$$

$$Y_t(p,q,b) = \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{i=1}^{q} \theta_i \upsilon_{t-q} + \upsilon_t + \sum_{i=1}^{b} \beta_i X_{it}$$

where Y_t, or $Bitcoin\_R_t$, is a stationary time series, - Eq. (2)

υ_t is a white noise process with $E(\upsilon_t) = 0; E(\upsilon_t^2) = \sigma^2; E(\upsilon_t \upsilon_s) = 0, t \neq s$

and X_t is an exogenous variable.

Second, we switch our focus from Bitcoin returns to Bitcoin volatilities (BVOL) to determine if BVOL can be explained by the volatilities of the S&P500 (VIX) and gold (GVOL) using a GARCH (p, q), model as developed by Engle (1982) and Bollerslev (1986) using Equation (3).

$$\sigma^2_{BVOL(t)} = \alpha_0 + \sum_{i=1}^{p} \beta_i \sigma^2_{BVOL(t-i)} + \sum_{j=1}^{q} \alpha_j \mu^2_{t-j} \qquad \text{- Eq. (3)}$$

where $\sigma^2_{BVOL(t)}$ is the conditional variance of μ_t since it is one period ahead estimate based on past information, and $\mu_t \sim N(0, \sigma^2_{BVOL(t)})$. α_j and β_i are positive to ensure that conditional variance is positive. When q=0, the GARCH model reduces to the ARCH model. $Y_t = C + \mu_t$ where C is the mean of Y_t, and μ_t is i.i.d. with mean zero. To allow for conditional heteroscedasticity, $Var_{t-1}[\mu_t] = \sigma_t^2$.

Third, Vector Autoregression (VAR), a stochastic process model, is used to capture the linear interdependencies among multiple time series (returns of Bitcoin, S&P 500, and Gold). Given any two-stationary series (y_1) and (y_2), we can test if (y_1) causes (y_2) by checking how much of the current (y_2) can be explained by past values of (y_2) and then checking to see whether addition of lagged values of (y_1) can help improve the explanation. In other words, if the coefficients on the lagged (y_1)'s are statistically significant, (y_2) is said to be Granger caused by (y_1). According to Sims (1980), if there is simultaneity among a number of variables, then all these variables should be treated in the same way. In other words, there should be no distinction between endogenous and exogenous variables. Therefore, once this distinction is abandoned, all variables are treated as endogenous. This means that in its general reduced form, each equation has the same set of regressors, which leads to the development of VAR models. The VAR model approach has some desirable characteristics as outlined in Asteriou (2011). VAR models generalize the univariate AR model by allowing for more than one evolving variable. All variables in a VAR enter the model in the same way: each variable has an equation explaining its evolution based on its own lagged values, the lagged values of the other variables, and an error term. VAR model does not require as much knowledge about the forces influencing a variable as do structural models with simultaneous equations. The only prior knowledge required is a list of variables which can be hypothesized to affect each other intertemporally. We use a Pth order VAR, denoted by VAR(p) or Y_t, as shown in Equation (4).

$$Y_t = C + \prod_1 Y_{t-1} + \prod_2 Y_{t-2} + \ldots + \prod_p Y_{t-p} + \mu_t, \ \ \mathrm{t} = 1, \ldots, \mathrm{T}$$

where Y_t=$(Y_{1,t}, Y_{2,t}, \ldots, Y_{n\text{-}t})'$ is a $k \times 1$ vector of time series variables, $\prod_i$ are $k \times k$ matrices of coefficients, C is a $k \times 1$ vector of constants, and μ_t is a $k \times 1$ unobservable white noise vector process. $E(\mu_t) = 0, E(\mu_t \mu_{t-k}^{'}) = 0$ for any non-zero k. - Eq. (4)

Bitcoin return in a VAR(p) model is treated as being contemporaneously exogenous matrix Y_t, as shown in Equation (5).

$$Y_t = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{pmatrix} BitCoin\_R \\ SP500\_R \\ Gold\_R \end{pmatrix} \qquad \text{- Eq. (5)}$$

Finally, we test for Granger causality among our variables. Granger causality (1969) has been used extensively to test the direction of causality between two variables. Before conducting any tests on Granger causality, it is important to study the time series properties of our variables. Granger and Newbold (1974) posit that spurious regression problems occur if there is non-stationarity in data, and this leads to unreliable correlations within regression analysis. We determine if our data is stationary and cointegrated by testing for unit roots in the data using Augmented Dickey-Fuller

Tests. Based on the results of unit roots tests, we then test for cointegration using Johansen's (1991) methodology.

RESULTS

In this section, we summarize the results based on the methodology described in Section 3. We focus on forecast accuracy of returns, volatilities, and causality. We show in the next three subsections that Bitcoin returns are difficult to predict, Bitcoin volatility can be estimated using a GARCH model, and gold returns have "Granger caused" Bitcoin returns.

Bitcoin return

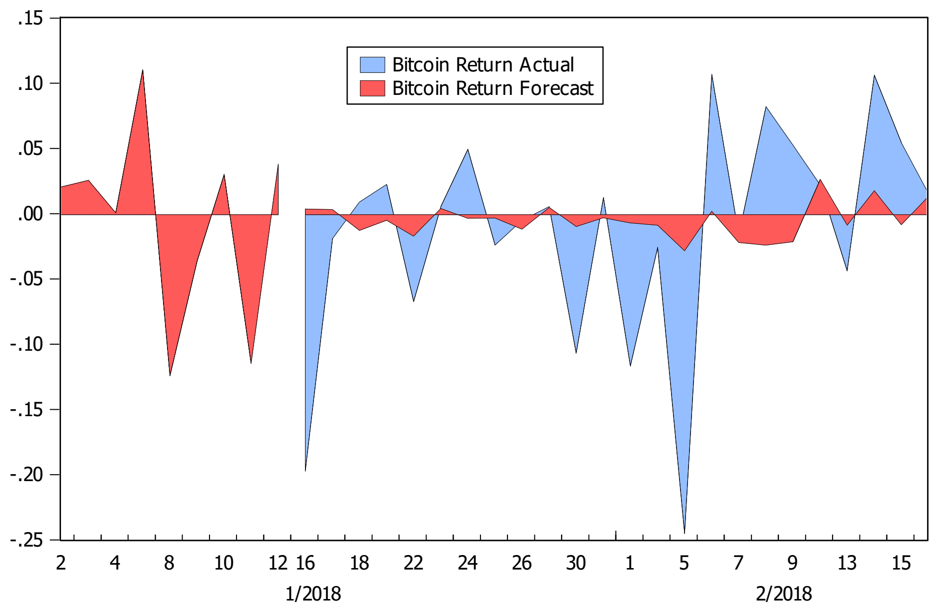
As expected, prices are non-stationary for all three asset classes (i.e. Bitcoin, S&P500, and Gold) used in this study. However, returns are stationary at the 5% significance level for all of them. Consequently, we used an ARMAX model to forecast returns. ARMAX models contain autoregressive (AR), moving average (MA), and additional explanatory variables (ex: gold) guided by economic theory. Compared to a multiple regression model (which does not account for AR and MA components), we found that ARMAX (4,4,2) model best describes Bitcoin returns using in-sample and out-of-sample analysis. Bitcoin returns are clustered as shown in Table (3), and we notice strong auto correlation and moving average coefficients for four days in the forecast. Forecasting Bitcoin returns, a highly volatile series with a standard deviation 10 times higher than mean, $\sigma_t = 10 \times \mu_t$, is challenging.

We used out-of-sample forecasting method and split the available data (from 7/19/2010 to 2/16/2018) into two groups. Data from 7/19/2010 to 1/16/2018 are used for model estimation and from 1/16/2018 to 2/16/2018 are used for model forecasts. Actual and forecasted value of bitcoin returns are shown in Figure (4). It is quite evident that the model forecasts direction of returns accurately but misses the magnitude. It appears that Bitcoin return predictability is not an easy job. Our finding is in line with Welch and Goyal (2008) who found that by and large, predictors of the equity premium models have predicted poorly both in-sample (IS) and out-of-sample (OOS) over a thirty-year period until 2008. Our findings are also consistent with the findings of Bariviera (2017, p. 7) who found that Bitcoin daily return after 2014 "seems to be compatible with a white noise". Finally, another similar finding is reported in Balcilar, Bouri, Gupta, and Roubaud (2017, p. 19) who stated that "when the market is performing well or poorly, all that matters for predicting future returns is past values, and thus information about volume is irrelevant." Since Bitcoin prices as shown in Figure (1) illustrate abnormal price hikes and crashes, even adding volume as a predictor will not help in forecasting Bitcoin returns. Our method goes beyond the bivariate method used by Balcilar et all (2017, p. 20) in that we use multivariate approach and check the robustness of results using out-of-sample forecast.

Table 3. Bitcoin Return forecast based on the ARMAX (4,4,2) model from 07/19/2010 to 01/16/2018. Dependent Variable: BITCOIN_R, Method: ARMA Maximum Likelihood (OPG - BHHH), observations: 1887, Convergence achieved after 111 iterations

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	0.0059	0.0027	2.1708	0.0301
SP500_R	0.3119	0.1317	2.3684	0.0180
GOLD_R	0.3628	0.1147	3.1631	0.0016
AR (1)	(0.3777)	0.0927	(4.0723)	0.0001
AR (2)	0.1825	0.0971	1.8793	0.0604
AR (3)	0.2632	0.0868	3.0308	0.0025
AR (4)	0.6369	0.0918	6.9366	0.0001
MA (1)	0.3861	0.0986	3.9181	0.0001
MA (2)	(0.1705)	0.1041	(1.6381)	0.1016
MA (3)	(0.2019)	0.0908	(2.2227)	0.0264
MA (4)	(0.5269)	0.0960	(5.4897)	0.0001
SIGMASQ	0.0043	0.0001	65.6094	0.0001
Log likelihood	2,458.37	**Prob(F-statistic)**	0.0001	
F-statistic	5.5555	**Durbin-Watson stat**	1.9488	

Figure 4. Realized and estimated Bitcoin returns from 1/16/18 to 2/16/18



As described in detail by Brownlees, et al (2011), realized volatility models often demonstrate excellent forecasting performance. So, we turn our attention to forecasting volatilities in the next subsection.

Bitcoin volatility

Return volatility is central to financial economics. Andersen et al (2006) provide a comprehensive theoretical overview on volatility forecasting. Volatility is inherently unobserved, or latent, and evolves stochastically through time. Not only is there nontrivial uncertainty to deal with in financial markets, but the level of uncertainty is latent. The current interest in volatility modeling and forecasting was spurred by Engle's (1982) ARCH paper, which set out the basic idea of modeling and forecasting volatility as a time-varying function of current information. The GARCH class of models, of which the GARCH (1,1) remains the workhorse, were subsequently introduced by Bollerslev (1986), and discussed independently by Taylor (1986). We compute Bitcoin realized volatilities as described in Section 3.B using both the GARCH (1,1) and ARMAX (3,1,2) models. To be consistent, we use the same methodology to compute volatility on gold prices and use VIX as a proxy for stock volatility. Results of the GARCH (1,1) and ARMAX (3,1,2) models are shown in Tables (4) and (5).

Table 4. Bitcoin volatility forecast based on the GARCH (1,1) model from 07/19/2010 to 01/16/2018. Method: ML ARCH, normal distribution (BFGS/Marquardt)
Included observations: 1910 after adjustments, Convergence achieved after 22 iterations
GARCH = C (1) + C (2) *RESID (-1) ^2 + C (3) *GARCH (-1)

Variance Equation	Coefficient	Std. Error	z-Statistic	Prob.
C	0.0001	0.0000	7.5371	0.0000
RESID (-1) ^2	0.1669	0.0100	6.7337	0.0000
GARCH (-1)	0.8289	0.0067	23.0956	0.0000
Log likelihood	2,880			
Durbin-Watson stat	1.908			

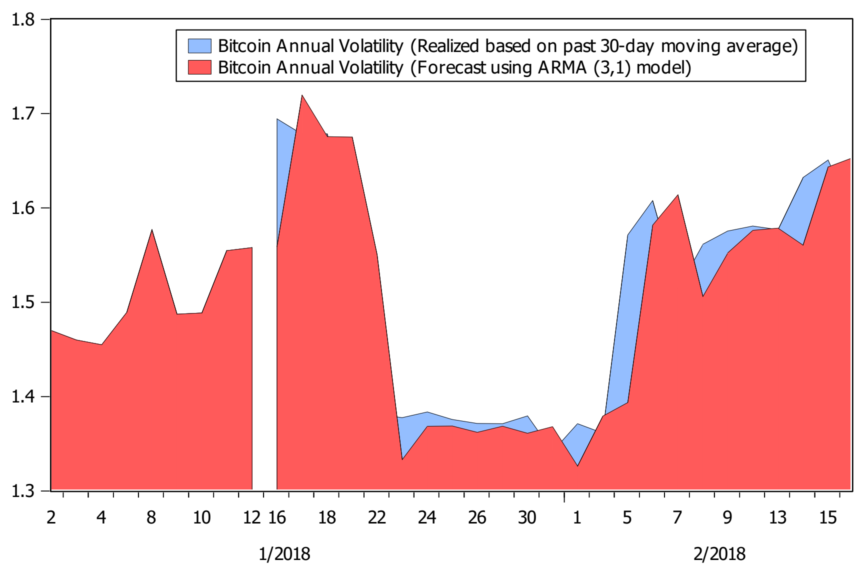
GARCH coefficient of 0.8289 indicates Bitcoin volatility clustering, or large values of $\sigma^2_{BVOL(t-1)}$ are followed by large values of $\sigma^2_{BVOL(t)}$ and small values of $\sigma^2_{BVOL(t-1)}$ are followed by small values of $\sigma^2_{BVOL(t)}$. A further analysis using T-GARCH (1,1,1) model (results not shown here, but available from authors) shows that threshold term is negative, indicating that negative shocks (good news) decrease the volatility or positive shocks (bad news) increase the volatility. The impact of positive shocks (bad news) is more severe and therefore causes more volatility. As shown in Table (2), correlation between BVOL and GVOL is 0.34 and between BVOL and VIX is 0.29. It implies that a significant part of Bitcoin volatility is unrelated to those factors that cause stock price volatility or gold volatility. Since Bitcoin is considered a 'digital gold', any BVOL that can't be explained by GVOL must be originating from Bitcoin's demand-side unsystematic risk.

Table 5. Bitcoin volatility forecast based on the ARMAX (3,1,2) model from 07/19/2010 to 01/16/2018. Method: ML ARCH, normal distribution (BFGS/Marquardt)
Included observations: 1910 after adjustments, Convergence achieved after 22 iterations
BVOL = C + C(2)*VIX + C(3)*GVOL + [AR(1)=C(4),AR(2)=C(5),AR(3)=C(6),MA(1)=C(7)]

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	0.9544	0.1463	6.5223	0.0001
VIX	0.0022	0.0008	2.7792	0.0055
GVOL	0.5455	0.0919	5.9348	0.0000
AR (1)	2.0626	0.0494	41.7832	0.0000
AR (2)	(1.2035)	0.0746	(16.1372)	0.0000
AR (3)	0.1388	0.0267	5.1979	0.0000
MA (1)	(0.8529)	0.0443	(19.2362)	0.0000
SIGMASQ	0.0056	0.0001	101.9265	0.0000
Log likelihood	2,186	**Hannan-Quinn criter.**	(2.3317)	
Probability of F-stat.	0.0000	**Durbin-Watson stat**	2.0002	

Next, we use out-of-sample forecasting method with training data from 7/19/2010 to 1/16/2018 and forecast BVOL from 1/16/2018 to 2/16/2018. Actual and forecasted values of are shown in Figure (5). It is evident that the model forecasts both the direction and the magnitude of volatility. Forecasting Bitcoin volatility is more precise compared to its returns.

Figure 5. Realized and estimated Bitcoin volatility from 1/16/18 to 2/16/18



VAR and Granger Causality Tests

The VAR model approach has some desirable characteristics as outlined in Asteriou (2011). First, it is very simple. The econometrician does not have to worry about which variables are endogenous or exogenous. Second, estimation is also very simple, in the sense that each equation can be estimated separately with the usual OLS method. Third, forecasts obtained from VAR models are in most cases better than those obtained from the far more complex simultaneous equation models. Results of the VAR model as specified in Equation (5) are shown in Table (6) below.

Table 6. VAR model estimation of linkages between Bitcoin, S&P 500 and Gold from 07/19/2010 to 02/16/2018. Included observations: 1908 after adjustments
Standard errors in () & t-statistics in []

	BITCOIN_R	SP500_R	GOLD_R
BITCOIN_R (-1)	0.0338	0.0021	0.0032
	(0.0230)	(0.0031)	(0.0036)
	[1.4738]	[0.6623]	[0.8860]
BITCOIN_R (-2)	0.0289	(0.0008)	(0.0030)
	(0.0229)	(0.0031)	(0.0036)
	[1.2627]	[-0.2609]	[-0.8376]
SP500_R (-1)	0.0822	(0.0488)	0.0291
	(0.1694)	(0.0230)	(0.0266)
	[0.4849]	[-2.1278]	[1.0942]
SP500_R (-2)	(0.1324)	0.0240	0.0143
	(0.1695)	(0.0230)	(0.0266)
	[-0.7810]	[1.0472]	[0.5393]
GOLD_R (-1)	0.3825	(0.0028)	(0.0236)
	(0.1464)	(0.0198)	(0.0230)
	[2.6129]	[-0.1418]	[-1.0293]
GOLD_R (-2)	0.0606	0.0250	(0.0340)
	(0.1466)	(0.0199)	(0.0230)
	[0.4135]	[1.2605]	[-1.4789]
C	0.0058	0.0005	0.0000
	(0.0015)	(0.0002)	(0.0002)
	[3.7340]	[2.3622]	[0.1936]

We highlight three points from the results. First, only the past gold returns have a statistically significant impact on the Bitcoin returns. One might say that Bitcoin return tracks physical gold return. Second, Bitcoin return does not appear to be influenced by the stock market. One might conclude that investors are not rushing to buy Bitcoins when the stock market turns volatile. Finally, as one would expect, Bitcoin return has no impact on the Stock market return. Bitcoin is still a small fraction of the market cap of the S&P 500 to have any influence on it.

Some researchers such as Blau (2017) tried to discover those factors that influence Bitcoin price boom and bust patterns. As an example, in their study they observed that "Bitcoin remained well below $20 from September 2010 to the beginning of 2013. In 2013, the value of Bitcoin was as low as $13 and as high as $1,132. In the months that followed the spike in Bitcoin's value, the digital currency lost approximately 60% of its value." They tested the assumption that speculative trading was behind the Bitcoin price gyrations. However, they stated that "finding that speculative trading is not driving the presence of excess volatility in Bitcoin is puzzling and suggests that something other than speculation is responsible for the observed bubble in Bitcoin and its volatility." To shed light on these factors behind Bitcoin returns, we conduct Granger causality tests and show the results in Table (7) below. Results support the previous claim that only gold returns have a statistically significant (at 95% confidence interval) impact on Bitcoin returns. We do not find any other causality effect in either direction. Consequently, we conclude that as shown in Table (6), previous-day gold returns can explain 38.25% of the Bitcoin's current-day returns. The factors behind gold returns (such as a hedge, a safe haven for stocks, not safe haven for bonds, etc.) are explained by other researchers such as Baur and Lucey (2010) and Baur and McDermott (2017). It means that there are additional factors (beyond the stock market, physical gold, speculative trading, and safe haven for stocks) driving Bitcoin returns. Discovering these other factors that drive Bitcoin returns can be a future research topic.

Table 7. VAR model estimation of linkages between Bitcoin, S&P 500 and Gold from 07/19/2010 to 02/16/2018. Included observations: 1908 after adjustments
VAR Granger Causality/Block Exogeneity Wald Tests

	Chi-square	**df**	**Prob.**
Dependent variable: BITCOIN_R			
SP500_R	0.8864	2	0.6420
GOLD_R	6.9473	2	0.0310
Dependent variable: SP500_R			
BITCOIN_R	0.4966	2	0.7801
GOLD_R	1.6193	2	0.4450
Dependent variable: GOLD_R			
BITCOIN_R	1.4420	2	0.4863
SP500_R	1.4313	2	0.4889

CONCLUSION

In this paper, we conduct time-series analysis of the returns and volatilities of Bitcoin price, Stock market (S&P 500 index), and gold price. We use the Autoregressive-moving-average model with exogenous inputs model (ARMAX), Generalized Autoregressive conditionally heteroscedastic (GARCH) model, Vector autoregression (VAR) model, and Granger causality tests to determine linkages between the S&P500, gold, Bitcoin prices, and their respective returns, and volatilities. Our models developed in this paper forecast the direction of returns accurately but miss the magnitude. However, our models forecast the direction as well as the magnitude of volatility accurately. We also find that Bitcoin volatility is clustered, negative shocks (good news) decrease the volatility, and positive shocks (bad news) increase the volatility. In terms of causality, we find that only past gold returns have a statistically significant impact on the Bitcoin returns and Bitcoin return has no impact on the Stock market return.

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