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Highlights (for review)

- We evaluate the adaptive market hypothesis (AMH) in Bitcoin market.
- Linear and nonlinear dependence checked using rolling-window approach.
- Efficiency evolves with emergence of events and adheres to the AMH proposition.

Title Page

Adaptive market hypothesis and evolving predictability of Bitcoin

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Abstract

This study evaluates the adaptive market hypothesis (AMH) and evolving return predictability in in bitcoin market. We use two robust methods in a rolling-window framework to capture time-varying linear and nonlinear dependence in bitcoin returns. We find that market efficiency evolves with time and validates the AMH in bitcoin market.

Keywords: Adaptive market hypothesis (AMH), bitcoin, martingale difference hypothesis.

JEL Classification: G01, G14, G12.

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1. Introduction

In the domain of economics and finance, there is extensive literature on the martingale difference hypothesis (MDH), a linchpin theory. The MDH asserts that asset price reacts to new information immediately, and follows the martingale difference sequence (MDS). Since Fama (1970), studies on the efficient market hypothesis (EMH) have tested the MDH and random walk hypothesis (RWH).[2] If the market adheres to weak form efficiency, as per the EMH, the asset price follows the martingale sequence—the current price does not follow its past trend, and becomes mean-independent.

Behavioral economists believe that the EMH framework cannot explain why market efficiency varies over time, and that market efficiency can be influenced by change in market conditions, the number of competitors, composition of investors, profit opportunities, and the risk–reward relationship. Nevertheless, EMH proponents assume a market is frictionless, and consider market efficiency immutable and a static phenomenon.

Lo (2004) derives an alternative theory—the adaptive market hypothesis (AMH)—from evolutionary principles such as competition, adaptation, and natural selection to bring unanimity between two spectrums. The AMH asserts that markets evolve and—because of events and structural changes, adapt—and market efficiency varies in degree at different times (Lo, 2005). It is unrealistic to expect perfectly efficient/inefficient markets—due to behavioral bias—as per the EMH. The importance of AMH is well documented (Charles et al., 2012; Hiremath and Narayan,

[2] To understand the difference between martingale process and random walk, see Escanciano and Lobato (2009).

2016). Against this backdrop, this study has used the AMH framework, for the first time, to assess the evolution of bitcoin, the most popular digital currency.

Bitcoin has received substantial attention from investors, speculators, and policymakers. As on 26 December 2017, it topped 1,382 cryptocurrencies in market capitalization and volume of trade, and had 44.8 per cent market share (Cryptocurrency Market Capitalizations, 2017). Bitcoin lacks supervision—unlike the stock market—and functions round the clock. Its price movement witnesses abnormal growth and volatility. There have been many hacking attempts in the past five years, and changes in policy and the market. With the evidence of institutional and operational heterogeneity, it can be useful to evaluate AMH in the bitcoin market. We contribute to the existing literature on bitcoin in the following ways.

First, we examine the AMH for bitcoin. It will be illusory to accept the static condition of market efficiency, as pronounced by the EMH, for an emerging market like bitcoin—where structural, operational, and environmental changes are expected to be frequent. There are a few studies on the EMH of bitcoin (Urquhart, 2016; Nadarajah and Chu, 2017; Bariviera, 2017; Tiwari et al., 2017; Jiang et al., 2017), but none on the AMH.

Second, we implement the Dominguez-Lobato (DL) consistent test and generalized spectral (GS) test in a rolling window framework to test the MDH and capture evolving linear and nonlinear dependence in bitcoin prices. There are studies that measure the time-varying long memory of the bitcoin market (Bariviera 2017; Tiwari et al., 2017; Jiang et al., 2017), but no study measures time-varying linear and nonlinear dependence. Time-varying long memory examines the presence of varying long-range or temporal persistence, whereas time-varying linear and nonlinear approaches explore the existence of evolving short-range predictability.

The paper structured as follows: Section 2 presents data and descriptive statistics. Section 3 describes methods performed. Section 4 and 5 outlines results and conclusion, respectively.

2. Data

This study uses the daily bitcoin price from July 18, 2010 to December 21, 2017—retrieved from https://www.coindesk.com/price for the period, and comprising 2,714 observations (Figure 1). Data availability guided the selection of the study period. We convert the raw data in logarithmic returns through $R_t = ln\left(\frac{P_t}{P_{t-1}}\right) * 100$ for estimation. The descriptive statistics of bitcoin returns document positive mean return and higher standard deviation (Table 1). We find excess kurtosis and negative skewness. The significant Jarque-Bera and other similar statistics reported reveals non-normality of dataset, and Augmented-Dickey-Fuller (ADF) statistics confirm stationarity. Additionally, Ljung-Box-Q and ARCH-LM statistics indicate the presence of serial correlation and conditional heteroscedasticity, respectively, at lag 12.

[About here Table-1 and Figure-1]

3. Methods

To test MDH in the bitcoin market, this study follows the consistent test of Dominguez and Lobato (2003) and the GS of Escanciano and Velasco (2006). According to Charles et al. (2012), the DL and GS tests—unlike other linear and nonlinear methods—do not have the issue of size distortions, and deliver robust output under the condition of non-normality and heteroscedasticity. The bitcoin returns show negatively skewed excess kurtosis, conditional heteroscedasticity, and evidence against normality (Table 1). Therefore, considering bitcoin data features, we adopt the DL and GS tests, which suit to time series that exhibit non-normality and heteroscedasticity (Charles et al., 2012). The DL test is a linear and nonlinear method test for existence of directional predictability in time series data. The Cramervon-Mises and Kolmogorov-Smirnov statistics form the base of the DL test, and are expressed as:

$$CvM_{T.p} = \frac{1}{\hat{\sigma}^2}\sum_{j=1}^{T}\left[\sum_{t=1}^{T}(Y_t - \bar{Y})1(\tilde{Y}_{t.p} \le \tilde{Y}_{j.p})\right]^2 \qquad (1)$$

$$KS_{T.p} = max_{1\le i\le T}\left|{}^{1}\!/_{\hat{\sigma}\sqrt{T}}\sum_{t=1}^{T}(Y_t - \bar{Y})1\left(\tilde{Y}_{t.p} \le \tilde{Y}_{j.p}\right)\right| \qquad (2)$$

where p is the positive integer and $\tilde{Y}_{t.p} = (Y_{t-1}, \dots \dots Y_{t-p})$ is the indicator function.

The GS test assumes dependence at all lags, allows conditional heteroscedasticity, and is consistent with extensive independent and identically distributed sequences. The spectral distribution function of the GS test—proposed by Escanciano and Velasco (2006), to test the null of martingale sequence—is expressed as:

$$H(\lambda,\chi) = \gamma_0(\chi)\lambda + 2\sum_{j=1}^{\infty}\gamma_j(\chi)\frac{sin(j\pi\lambda)}{j\pi}, \qquad (3)$$

where λ is the any real number between [0,1].

The GS distribution function follows the value $H_0(\lambda,\chi) = \hat{\gamma}_0(\chi)\lambda$, and the statistics followed to test the null of dependence is as follows:

$$S_T(\lambda,\chi) = (0.5T)^{\frac{1}{2}}\{\hat{H}\ (\lambda,\chi) - \hat{H}_0(\lambda,\chi)\} \qquad (4)$$

To estimate the distance between $S_T(\lambda,\chi)$ and zero for all possible values of λ and χ Escanciano and Velasco (2006) follow the Cramer-von Mises norm and suggests to obtain D_n^2 statistics.

$$D_n^2 = \sum_{j=1}^{n-1}\frac{n-j}{(j\pi)^2}\sum_{t=j+1s}^{n}\sum_{=j+1}^{n}\left(Y_t - \bar{Y}_{n-j}\right)\left(Y_s - \bar{Y}_{n-j}\right)\exp\left[\left(Y_{t-j} - Y_{s-j}\right)^2\right] \qquad (5)$$

The null hypothesis of this test is rejected when the value of D_n^2 is relatively large.

4. Results

[About here Figure-2 and Figure-3]

To obtain the evidence on evolving efficiency of bitcoin price movement, we use a fixed-length rolling window of 400 observations.[3] Estimated p-values of DL and GS test for rolling windows are presented in Figures 2 and 3, respectively.

A horizontal line parallel to the x-axis at points 0.05 and 0.10 denote the level of significance at 5 per cent and 10 per cent, respectively. P-values that fall on or under that line mean inefficiency. Broadly, the evidence of swings in efficiency in Figures 2 and 3 lend support for the AMH. Particularly, results from the DL and GS tests show a heightened period of efficiency from mid-2012 to November 2013, and then 2015 onwards, and inefficiency from August 2011 to August 2012 and from December 2013 to December 2014.

We—unlike past studies on bitcoin efficiency—identify events that coincide with episodes of efficiency and, possibly, influence its dynamics. Studies available in similar line for stock markets (Hiremath and Kamaiah, 2010) and forex markets (Charles et al., 2012) follow a similar approach and hold that events that coincide with efficiency/inefficiency may influence dynamics of efficiency. Thus, we survey reports, the news, and the literature to identify bitcoin-related events, such as crime, hacking, technology, policy alteration, and market orientation.

Inefficiency during August 2011 and August 2012 can be ascribed to the hacking of Linode, an American server, which caused the loss of 46,000 bitcoin, and in 2012 of Bitfloor, a major exchange dealing with US dollars, which led to the loss of 24,000 bitcoin. The failure of Bitcoin Savings & Trust, a Ponzi scheme, may have scared holders of bitcoin and prospective investors, and led to predictability. The establishment of the Bitcoin Foundation in September 2012—to

[3] We choose a window long enough to hold power and size properties of test, and to identify short-lived predictability. We take window length of 300, 400, and 500, and use seven-day rolling, to avoid computational complexities, and observe that our results are not sensitive to window length. Results of 300 and 500 window size are available from the authors on request.

promote, protect, and standardize the open source protocol in bitcoin—and the increasing acceptance of bitcoin, as revealed by Bitpay, a payment processing service, may have caused the efficiency observed from mid-2012 to November 2013. The predictability documented from December 2013 to December 2014 may have been the outcome of several events—Mt. Gox, a major bitcoin exchange, suspended trading in February 2014, and subsequently declared bankruptcy; and authorities, like the Russian and Chinese central banks and the Japanese government, prohibited financial institutions and legal entities from dealing in bitcoin.

The period of efficiency since 2015 can be ascribed to the policy shift in favor of bitcoin in Europe, Japan, and Russia, and the recent trend (Figures 2 and 3) to the herding behavior of participants, due in turn to the abnormal movement of bitcoin prices. Thus, investors should devise a trading strategy to make extra returns before the predictability disappears, and policymakers should plan to restore efficiency.

This study finds that linear and nonlinear dependence evolves with time. This finding resembles that of Bariviera (2017) and Tiwari et al. (2017)—which document evidence of time-varying long-range dependence—but contradicts the finding of Jiang et al. (2017). Our findings corroborate that of Caporale and Plastun (2017), which evidences episodes of efficiency for emerging cryptocurrencies Litecoin, Ripple, and Dash, although there is evidence of significant inefficiencies. Our finding that efficiency/inefficiency evolves with emergence of market frictions is supported by Caporale and Plastun (2018) on abnormal behavior in cryptocurrency markets. However, our finding contradicts Brauneis and Mestel (2018), who study 73 cryptocurrencies, including bitcoin, in line with the EMH, and conclude that the market is either efficient or inefficient.

5. Conclusion

This study verifies the evolving efficiency in the movement of bitcoin prices, and concludes that the evidence of dynamic efficiency adheres to the proposition of the AMH. Some crucial events coincide with episodes of efficiency/inefficiency. Thus, the conclusion drawn in past studies—bitcoin price movement is either efficient or inefficient, as per the EMH framework—is not practically true. Existence of behavioral bias and creation of events can change efficiency. The unanimity in findings from the methods employed signifies the robustness of this study. It suggests that speculators and arbitrageurs can exploit extra returns, but not always. A further attempt along this line—by providing quantitative rigor toward the drivers of evolving efficiency—can be a significant addition to the existing literature.

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Figure

Figure 1- Trend of Bitcoin price (in US $) movement.

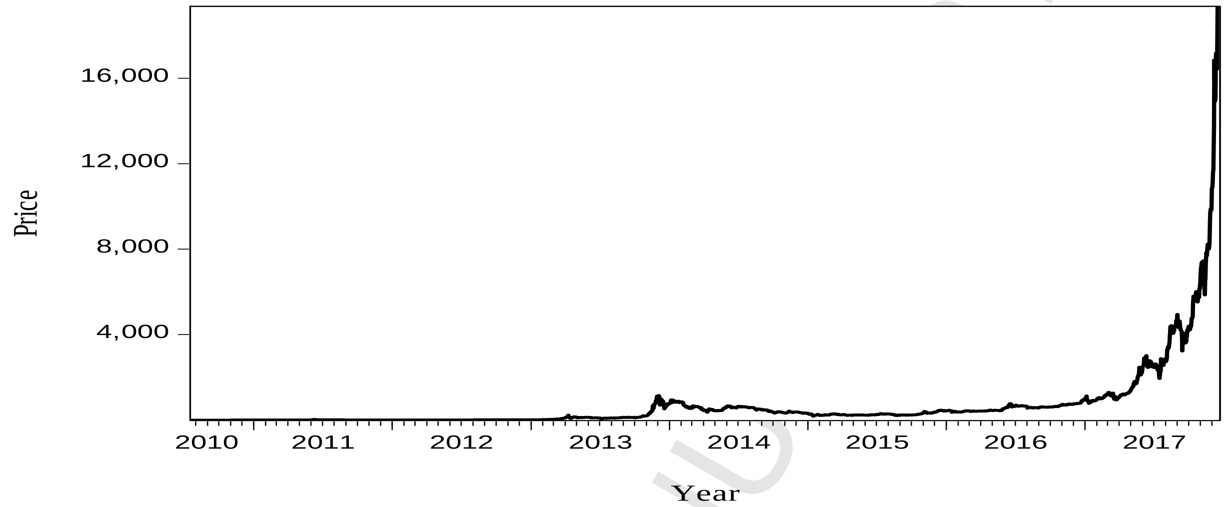


Figure 2 P-values of the Dominguez-Lobato consistent test.

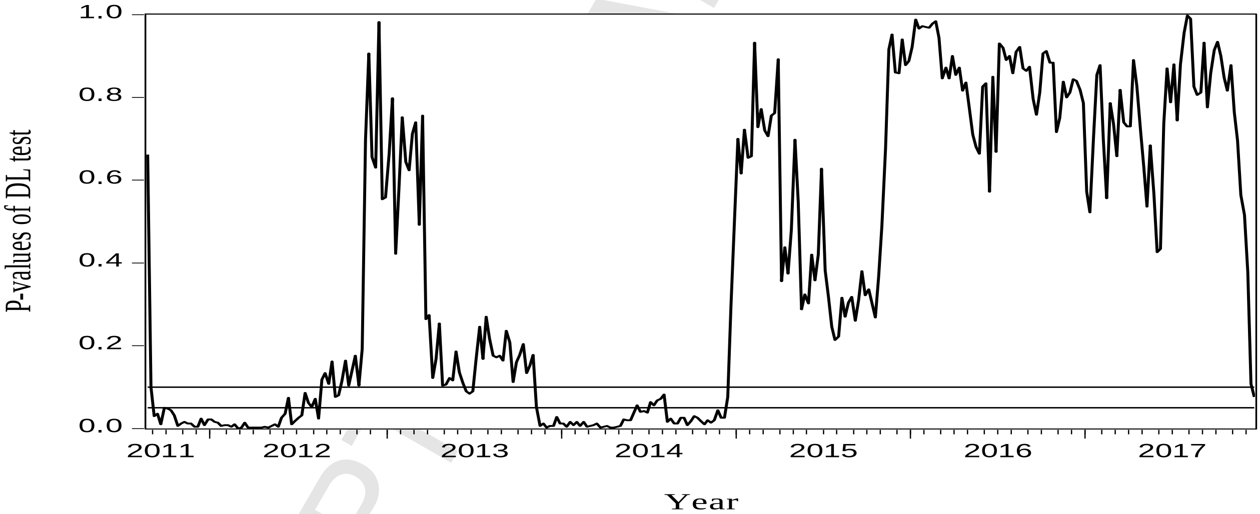
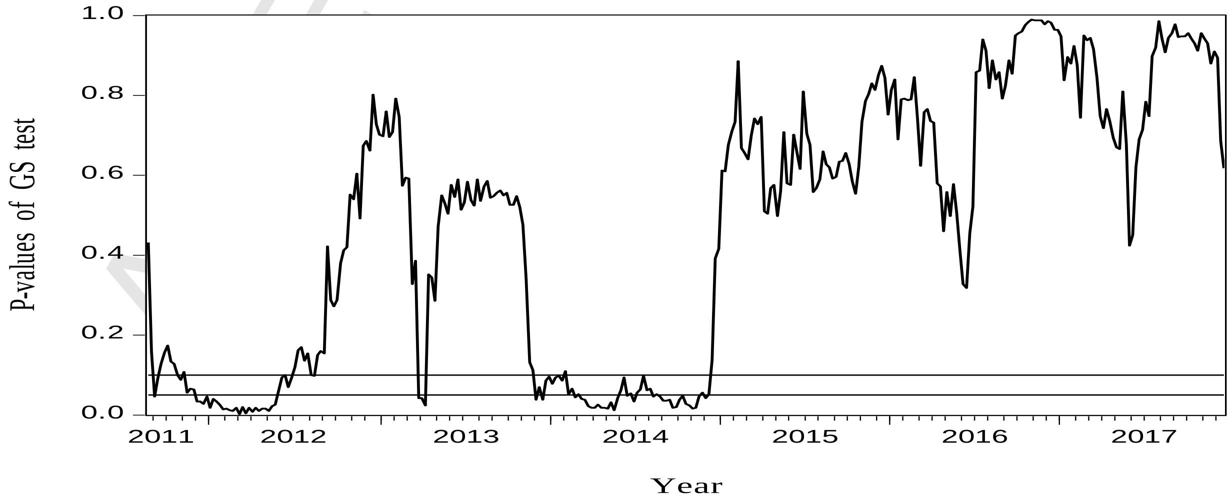


Figure 3- P-values of generalized spectral test.



Table

Table 1- Descriptive statistics of Bitcoin returns

Statistics	Bitcoin returns
Mean	0.444
Standard deviation	5.865
Skewness	-0.357
Kurtosis	15.233
Jarque-Bera	16975.08*
Kolmogorov-Smirnov	0.156*
Shapiro-Wilk	0.812*
ADF	-50.519*
Ljung-Box-Q (10)	59.174*
ARCH-LM (12)	869.000*

* denote significant at 1 % level.