

**Research Article**

Non-random walk in cryptocurrency: An empirical analysis of bitcoin

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ABSTRACT

The current study has examined the informational efficiency of market leader of cryptocurrency i.e, Bitcoin. The daily, weekly and monthly prices of Bitcoin have been used for analysis from 2013 to 2017. The information efficiency has been investigated by using different tests of random walk both parametric and non-parametric. The results indicate the Bitcoin returns are not weak form efficient and the element of random walk is not there. Hence, the investors have an opportunity to beat the market by using technical trading and get abnormal returns from the predictability of Bitcoin prices.

Keywords: *Bitcoin; Cryptocurrency; Random Walk; Efficient Market Hypothesis*

1. INTRODUCTION

Bitcoin and cryptocurrency have attracted the attention of investors and scholars during the phenomenal rise in the prices during the recent past. Nakamoto (2009) introduces a new form of financial asset named Bitcoin. It is a form of cryptocurrency, which is the blockchain-based electronic payment system. Since the inception of Bitcoin, it has gained a big following in electronic media, print media as well as academia. The main reason for the popularity of this new form of digital currency is the first decentralized currency based on blockchain technology. Bitcoin currency is derived from the mathematical cryptography called mining (Bradbury, 2013). Bitcoin is still to be considered a very young, even though 16 million of Bitcoins are already issued and having 21 million fixed number in total. Vranken (2017) argues that Bitcoin still requires more than a hundred years for the last coin to be mined and mining will be ceased in the year 2140.

Currently, Bitcoin has gained rapid market acceptability and there are no signs to be Wiped out soon (Chan et al., 2017). Bitcoins are considered as a market leader of cryptocurrencies, with the highest market capitalization. Selgin (2015) reports that investors are considering Bitcoin as a currency and investment option. It has got so much attention from investors due to its innovative features and transparency. Due to this popularity, the prices of bitcoin have risen to 12000% from the mid of 2013 to the end of 2017. Such lucrative features of bitcoin also have a threat of speculation and maybe the cause of the bubble and crash in

cryptocurrency markets. Due to such speculative behavior, Baek & Elbeck (2015) argue that it should be considered as a speculative commodity rather than currency.

The efficient market hypothesis (EHM) is a core concepts of finance regarding the informational efficiency of securities. The pioneer study of Bachelier (1900) has presented the theoretical idea and basic framework of EMH, with an argument about randomness in the commodity prices. The idea of EHM in financial markets i.e., informational efficiency has been given by Fama (1970) that financial asset prices must reflect all the information at a given point of time. Fama (1970) has divided the market efficiency into three kinds i.e., weak form, semi-strong form and the strong form of efficiency. Numerous studies have examined the informational efficiency in stock markets, that current price movements are predictable or not (Fama & French, 1988; Fraz & Hassan, 2016). However, cryptocurrency markets are not yet explored.

The current study is an effort to explore the efficiency dynamics of Bitcoin prices. Bitcoin has established itself as a leader in cryptocurrency by showing phenomenal growth in a couple of years. Some researches argue that it is a bubble due to the rise of Bitcoin prices in a short period of time. It is a need of time to check the price behavior of the newly emerged financial asset. This new form of a financial asset has provided a diversification opportunity to investors. So, the efficiency of Bitcoin should be investigated to provide guidelines for investors' protection. This study provides a better understanding for investors want to allocate their resources to Bitcoin as an alternative investment.

The rest of the paper has the following section: Section 2 presents the in-depth literature review about the subject. Section 3 presents the data description and methodological issues. Section 4 reports the data analysis and finally, section 5 presents the conclusion of the study.

2. LITERATURE REVIEW

The information plays a central role in the price determination of any financial assets. In recent years, researchers have shown special interest to understand the various characteristics and price dynamics of Bitcoins (Katsiampa, 2017; Hencic & Gouriéroux, 2015). Earlier studies have focused on the social feedback cycle, to form a link between the price of Bitcoin with social signals and the relationship between digital currencies and social trends by inquiring the queries on google and Wikipedia (Kristoufek, 2013; Moore & Christin, 2013). Hencic and Gouriéroux (2015) have used autoregressive model (non-causal) model to predict the exchange rate of Bitcoin to the US dollar. Cheah and Fry (2015) have argued that Bitcoin is not a true unit for a medium of exchange and a form to store value, because it is highly volatile and showed bubbles and crashes. Cheung et al., (2015) have also reported several short-time and long term bubbles in the bitcoin market.

Kondor et al., (2014) investigate the evolution of bitcoin transaction and its structure. The study reports that during the whole life of this system the distribution of wealth is heterogeneous. Glaser et al., (2014) examine the intra-network transactions to determine that Bitcoin is a financial asset or a currency. They have argued that Bitcoin is an asset because the first buyer of the Bitcoin is likely to hold it in the wallet for speculative purposes.

Moreover, the returns of Bitcoin react to the news events regarding digital currency and characterized in an asset class. Some studies argue that Bitcoin has the same abilities of hedging as compare to gold and currency (Dyhrberg, 2016a, 2016b).

The informational efficiency of Bitcoin has been the first time tested by Urquhart (2016). The study of Urquhart (2016) employs four tests Ljung-Box test, Runs test, MVR test and BDS test by using daily data from 2010 to 2016. The results of the study indicate that the Bitcoin market is inefficient. Further, the study has argued that the Bitcoin market is not mature. The transition phase of the market may be the reason for inefficiency. Nadarajah and Chu (2017) have extended the work of Urquhart (2016) by using eight different tests. The study has not used Bitcoin returns as used by the Urquhart study, they have used an odd integer power of the Bitcoin returns. They have argued that by powering the odd integer the information is not lost. The results of the study indicate that odd transferred Bitcoin returns are efficient.

The most recent study of Bariviera (2017) revisits the EMH and investigates the long memory of Bitcoin returns under time-varying behavior. The study has employed Hurst exponent and Detrended Fluctuation Analysis methodology by using daily price data of Bitcoins. The results of the study indicate that the market is efficient. Whereas, a recent study of Fraz et al., (2019) have investigated seasonality in the Bitcoin market and reported that the Bitcoin market is inefficient. Garcia et al., (2014) argue that it is not easy to detect the factors affecting the Bitcoin value. The study further reports that trust base cryptocurrencies can be influenced by social factors. According to the fundamental definition of EMH that "price reflects all the information". In connection with this argument, Kristoufek (2013) reports that every news in the media or the opinion of the general public is directly reflected by the Bitcoin market.

The growing interest of internet users in cryptocurrencies has determined the prices of Bitcoin (Kristoufek, 2015). Little (2014) suggests that the exchange of Bitcoins against goods and services can determine its value. The study argues that Bitcoins are not following the true e-commerce perspective, because most of the Bitcoins are instantaneously converted into traditional currency. Several studies argue that the extremely high volatility in the prices of Bitcoins are due to speculative investment or fundamental economic factors (Glaser et al., 2014; Buchholz et al., 2012). Even though, further growth of cryptocurrencies brings stability in the prices (Turpin, 2014). Bitcoin is an intangible thing and still a mystery for the general public that it can be used as a currency or not (Garcia et al., 2014).

As numerous studies have reported that Bitcoins offers diversification opportunities and hedging features similar to commodities, like gold and traditional currencies (Brière et al., 2015; Dyhrberg, 2016a). The global perspectives of the cryptocurrencies as an alternative to fiat currency and an investment market needs further insight. The current study is a contribution to the existing literature by shedding light on the informational efficiency of Bitcoins using multiple techniques for robustness.

3. METHODOLOGY

The data of bitcoin prices is collected for daily, weekly and monthly frequencies for the period of 1st may 2013 to 31 December 2017. The returns of all financial series are computed using the continuous compounding formula given below.

$$RB = \ln\left(\frac{PB_t}{PB_{t-1}}\right) \quad (1)$$

Where RB is the return of bitcoin, PB_t is the day end, weekend or month end price at time t and PB_{t-1} is the day end, weekend or month end price at time t-1. The data for the study has been collected from the website of cryptocurrency market capitalization.

To see the inefficiency dynamics in the bitcoin market different econometric test are applied in the current study. The summary statistics has been given in descriptive statistics and a set of different tests have been performed to examine the random walk behavior in bitcoin market. The normality tests are applied to investigate the distribution properties of the bitcoin series. The normally distributed data should follow a random walk (Fischer & Jordan, 1991), therefore Jarque-Bera and Kolmogorov-Smirnov tests are employed to confirm the normality assumption. The Jarque-Bera test checks the goodness of the fit and also analyze the normal distribution considering skewness and kurtosis. The formula of the Jarque-Bera (JB) test is as follows.

$$JB = \frac{N}{6} (SK^2 + \frac{1}{4} (KU - 3)^2) \quad (2)$$

Where N is the no. of observations of the financial time series, SK is the skewness of the series and KU is the kurtosis. Kolmogorov-Smirnov (KS) test also compares empirical and theoretical normal cumulative distribution. Kolmogorov (1933) has given the calculation of asymptotic distribution and Smirnov (1948) prepares the distribution table for the KS test. The formula of the KS test is as follows.

$$Z_o(y) = \frac{1}{N} \sum_{i=1}^N V_{Y_i \leq y} \quad (3)$$

Where Z_o is the distribution function, O is the autonomous and equally arbitrary distributed observation and $V_{Y_i \leq y}$ is dummy variable and captured indication by 1 and 0. The KS distribution function is given below.

$$D_o = \sup_x |Z_o(y) - Z(y)| \quad (4)$$

Where D_o is the function of cumulative distribution, $\sup_x$ is the supremum. In the case of the sample selection from the $Z(x)$ distribution under Glivenko Cantelli theorem assumption, the cumulative distribution function will converge closely toward 0. Gujrati (2008) has suggested that to fulfill the condition of stationarity the mean and variance of a financial series must be constant over time, which is a basic condition to test random behavior in financial time series. Two tests of stationarity are applied with the assumption

of constant variance over time with the independent error term (Dickey & Fuller, 1979) and heterogeneous distribution when error term is not independent (Phillips & Perron, 1988).

The simple form of autoregressive model i.e., AR(1) of Dickey and Fuller (1979) is used $y_t = Qy_{t-1} + \epsilon_t$. Where, y_t is the financial time series at time t , Q is the coefficient and ϵ_t is the disturbance term. The regression equation for the model is as follows.

$$\Delta X_t = \beta_1 + \beta_2 + (Q - 1)X_{t-1} + \sum_{i=1}^n \vartheta_i \Delta z^n_{t-1} + \epsilon_t \quad (5)$$

Where, X is the natural log of the variable of interest, t is the time trend term of the index, Q , ϑ represents the different parameters, Δ is the sign of change of the series at first order and ϵ_t is the disturbance term. Phillips and Perron (1988) have the same critical values as observed by the ADF test and the mathematical form of the PP test is as follows.

$$\Delta X_t = \psi_1 + \psi_2 X_{t-1} + \psi_3 \theta + \sum_{i=1}^n \psi_i \Delta X_{t-i} + \epsilon_t \quad (6)$$

Where X_t is the natural log of the Bitcoin series, θ is trend, both ψ and ψ represents the parameters, Δ sign is used to show the change of the series at first order and ϵ_t is the residual term. The autocorrelation coefficient test assumes a zero correlation with current and lag term. The basic mathematical form of the autocorrelation coefficient test is as follows.

$$RB_{i,t} = \alpha_i + \delta_j RB_{i,t-k} + \epsilon_{i,t} \quad (7)$$

Where $RB_{i,t}$ is return for a bitcoin “i” for given at time t , for constant α_i sign is used, $\epsilon_{i,t}$ is the disturbance or random error term and k is different time lags. For checking the overall randomness using multiple lags instead of individual lags Ljung & Box (1978) test is applied. The mathematical form of the Q-Ljung-Box autocorrelation test is as follows.

$$Q_{Ljung-Box} = N(N+2) \sum_{t=1}^i \frac{\psi^2(t)}{N-1} \quad (8)$$

Where N is the no. of observations at any difference and ψ is the set of collective sample autocorrelations up to the selected lag for time t . Runs test can be applied to non-normally distributed data to check serial dependence. A series is called random, if the expected runs of serial dependence should be near to actual runs. Wallis and Roberts (1956) have given the following mathematical form of runs test;

$$Z = \frac{(D - D_\mu)}{\sigma_{tk}} \quad (9)$$

Where D_μ is equal to $\frac{2m+m_-}{m} + 1$ and σ_{tk} is equal to $\sqrt{\frac{2m+m_- - (2m+m_- - m)}{m^2(m-1)}}$

Hence m represents the mean observations, $+m$ represents the positive returns and $-m$ represents the negative return, the sum of $+m$ and $-m$ represents the mean observations of the sample and $m = +m + -m$. Multiple variance ratio test (MVR) is developed by Chow

and Denning (1993) to check autocorrelation with the assumption of heteroscedasticity in financial time series of varying distribution. The formula of MVR test as given below.

$$VR(p) = \frac{\sigma^2(p)}{\sigma^2(1)} \quad (10)$$

Where $\sigma^2(p)$ is 1/pth variance of financial time series, $\sigma^2(1)$ is the variance at first differences and $VR(p)$ is 1 for the null hypothesis. Lo and MacKinlay (1988) propose an MVR test with two assumptions the first $Z^*(p)$ is a random walk increased with heteroscedasticity and $Z(p)$ is a random walk increased with homoscedasticity. The mathematical form for $Z^*(p)$ and $Z(p)$ stats with both assumptions are as follows.

$$Z^*(p) = \frac{\{VR(p) - 1\}}{\sigma_0(p)} \quad (11)$$

Where, $\sigma_0(p)$ is $\left[4 \sum_{k=1}^{p-1} \left(1 - \frac{k}{p}\right)^2 \delta_k\right]^{1/2}$ and $\delta_k = \frac{\sum_{i=k+1}^{mp} (q_i - q_{i-k-1} - p\hat{u})^2 (q_{i-k} - q_{i-k-1} - p\hat{u})^2}{[\sum_{i=1}^{mp} (q_i - q_{i-1} - p\hat{u})^2]}$

$$Z(p) = \frac{\{VR(p) - 1\}}{\sigma_0(p)} \quad (12)$$

Where $\sigma_0(p) = \{(2(2p-1)(p-1)/3p(np))^{1/2}\}$, MVR test is the combination of multiple variance ratios where $VR(p)$ is 1 of $MVR = VR(p) - 1 = 0$. If any of null hypothesis H_{0i} is rejected it rejects the assumption of random walk.

4. RESULTS AND FINDINGS

The statistical behavior of all return series on three frequencies of bitcoin series from May 2013 to December 2017 is reported in Table 1.

Table 1. Descriptive statistics of bitcoin returns from 2013 to 2017

	RBD	RBW	RBM
Mean	0.003	0.020	0.086
Median	0.002	0.008	0.076
Standard Dev.	0.044	0.124	0.309
Skewness	-0.111	-0.088	2.514
Kurtosis	11.998	7.507	14.822
Maximum	0.357	0.528	1.711
Minimum	-0.266	-0.519	-0.413

Note: RBD is the return of bitcoin for daily data, RBW is the return of bitcoin for weekly data and RBM is the return of bitcoin for monthly data

The results of the above table show that during the sample period the average return earned by the bitcoin in one month is higher than average daily and average weekly returns i.e., 8.6%, 0.30 %, and 2% respectively. The maximum loss of 41.3% in one month is observed, which is less than the loss reported in any week. At the same time, it is worth mentioning that in November 2013 the bitcoin prices are raised almost 200% and the price of bitcoin jumped from \$204 to \$1130. The monthly returns have earned a high return of 171% in one month with a high risk of 30.9% as compared to other two series of returns. The daily and

weekly returns have negative skewness, which is an indication that bitcoin market is dominant by negative returns as compare to positive returns. The monthly returns have positive skewness value and it is an indication of dominance of higher negative returns over positive returns. The return series are leptokurtic and peakier than the normal distribution. The Jarque-Bera test is applied to check the normality assumption. The results of the Jarque-Bera test along with observed and calculated values are given in table 2.

Table 2. Jarque-Bera test of bitcoin returns from 2013 to 2017

	RBD	RBW	RBM
JB (Observed Value)	5754.78	205.995	385.090
p-value at 1% significance level	0.000*	0.000*	0.000*

The results of table 2 indicate that the calculated value of the Jarque-Bera test is higher than the critical value of 5.991 for return at different frequencies, which shows it is different from zero. The rejection of the null hypothesis that residuals are normally distributed leads to the conclusion that the data is not normality distributed. The Kolmogorov-Smirnov (KS) also applied for normality to check the difference between underlying probability distribution and hypothesized distribution. Table 3 presents the results of the KS test.

Table 3. One-Sample Kolmogorov-Smirnov (K-S) Test of bitcoin returns from 2013 to 2017

		RBD	RBW	RBM
N		1705	243	56
Normal Parameters ^{a,b}	Mean	.003	.020	.086
	Std. Deviation	.044	.124	.309
	Absolute	.129	.107	.130
Most Extreme Differences	Positive	.109	.094	.130
	Negative	-.129	-.107	-.096
K-Z		5.326	1.669	.970
Asymp. Sig. (2-tailed)		.000	.008	.303

^a. Test distribution is Normal,

^b. Calculated from data

* indicates 1% significance level

The monthly return shows insignificant value, which show it is not fulfilling the normal distribution assumption. Whereas, the daily and weekly return series results are statistically significant that rejects the assumption of normality of data. Hence, the same conclusion can be drawn from the KS test. The stationarity results of unit root are given in table 4 using two assumption i.e., Augmented Dickey-Fuller (ADF) and Phillips Perron (PP).

Table 4. Results of ADF and PP of bitcoin returns from 2013 to 2017

ADF test statistic	RBD	RBW	RBM	PP test	RBD	RBW	RBM
Level	1.257	1.297	0.589	Level	1.056	1.027	0.589
1st difference	-41.140*	-13.447*	-6.939*	1st difference	-41.279*	-13.442*	-6.939*
At 5% **	-2.863	-2.873	-2.916	At 5% **	-2.863	-2.873	-2.916
At 1% **	-3.434	-3.457	-3.555	At 1% **	-3.434	-3.457	-3.555

* indicates 1% significance level

** Critical value

The results of the unit roots tests indicate that the calculated values for all financial series are less than the tabulated values. Hence it can be concluded that based on ADF and PP the returns are non-stationary. The results of the autocorrelation coefficient function are presented in table 5.

Table 5. Autocorrelation and Q-statics returns of bitcoin returns up to 10 lags from 2013 to 2017

Lags	1	2	3	4	5	6	7	8	9	10
Daily										
AC	0.003	-0.043	-0.005	0.046	0.047	0.072*	-0.019*	-0.016*	0.016*	0.051*
Q-Stat	0.021	3.154	3.192	6.826	10.581	19.373*	19.97*	20.416*	20.874*	25.323*
Prob	0.886	0.207	0.363	0.145	0.06	0.004	0.006	0.009	0.013	0.005
Weekly										
AC	0.14*	0.054	-0.007	0.012	0.038	0.078	-0.006	-0.032	-0.018	0.086
Q-Stat	4.831*	5.558	5.570	5.608	5.969	7.481	7.490	7.746	7.825	9.6936
Prob	0.028	0.062	0.135	0.23	0.309	0.279	0.38	0.459	0.552	0.468
Monthly										
AC	0.042	0.019	0.011	-0.053	-0.088	0.229	0.106	0.057	-0.085	-0.042
Q-Stat	0.104	0.125	0.132	0.306	0.798	4.190	4.933	5.1546	5.659	5.7848
Prob	0.747	0.939	0.988	0.989	0.977	0.651	0.668	0.741	0.773	0.833

* indicates 1% significance level

The results of autocorrelation tests indicate that no autocorrelation exists in monthly return up to 10 lags and no autocorrelation in daily return series up to 5 lags. For weekly returns, autocorrelation is found up to 1 lag and for daily returns series, the alternative hypothesis is accepted for 6 to 10 lags. The results on the basis of autocorrelation tests also confirm the element of predictability on the basis of past price behaviors and rejects the assumption of random walk for daily and weekly data. The Run test results for serial independence with non-parametric assumptions are given in table 6.

Table 6. Runs Test for changes in bitcoin returns from 2013 to 2017

	RBD	RBW	RBM
Test Value ^a	.002	.008	.076
Cases < Test Value	852	121	28
Cases >= Test Value	853	122	28
Total Cases	1705	243	56
Number of Runs	862	113	31
Z*	.412	-1.221	.539
Asymp. Sig. (2-tailed)	.680	.222	.590

Note: ^a indicates Mean, Z*- less than 1.96, then we can accept the null hypothesis

The run test results indicate that all return series have insignificant p-value, which rejects the hypothesis that no serial correlations exist. The total number of Runs are significantly lower than the total expected runs. The results MVR test for first null hypothesis “heteroscedasticity can increase randomness” are presented in table 7.

Table 7. Multiple variance ratio tests (Heteroscedasticity) of bitcoin returns from 2013 to 2017

	q	2	4	8	12	24	36
Daily Returns	VR (q)	0.522*	0.238*	0.127*	0.083*	0.043*	0.028*
	Z*(q)	-7.888	-7.504	-6.287	-5.667	4.518	-3.884
Weekly Returns	VR (q)	0.555*	0.289*	0.155*	0.099*	0.052*	0.031*
	Z*(q)	-4.051	-3.851	-3.365	-3.033	-2.403	-2.091
Monthly Returns	VR (q)	0.516	0.295	0.100	0.071	0.060	0.110
	Z*(q)	-1.605	-1.454	-1.457	-1.358	-1.197	-1.051

* 5% significance level

The daily and weekly returns have significant values of the Z* (q) statistic for period 2 to 36. The significance values of Z* (q) statistic show that both return series do not follow a random

walk. The values of $Z^*(q)$ statistic are insignificant for monthly return series, which leads toward the rejection of alternative hypothesis and accept the null hypothesis of random walk for monthly returns. The results of MVR test for second null hypothesis “homoscedasticity can increase randomness” are presented in table 8.

Table 8. Multiple variance ratio tests (homoscedasticity) of bitcoin returns from 2013 to 2017

	q	2	4	8	12	24	36
RBD	VR (q)	0.522*	0.238*	0.127*	0.083*	0.043*	0.028*
	Z(q)	-19.722	-16.808	-12.181	-10.095	-7.211	-5.916
RBW	VR (q)	0.555*	0.289*	0.155*	0.099*	0.052*	0.031*
	Z(q)	-6.930	-5.914	-4.446	-3.737	-2.691	-2.223
RBM	VR (q)	0.516*	0.295*	0.100*	0.071	0.060	0.110
	Z(q)	-3.586	-2.793	-2.257	-1.838	-1.272	-0.973

* 5% significance level

Note: RBD is the return of bitcoin for daily data, RBW is the return of bitcoin for weekly data and RBM is the return of bitcoin for monthly data

The daily and weekly returns have have significant values of the $Z^*(q)$ statistic for period 2 to 36 and for monthly returns, $Z^*(q)$ statistic is significant for period 2 to 8. The significance of $Z^*(q)$ statistic shows that daily, weekly and monthly return series does not follow a random walk. The summary of the overall results of efficiency is presented in table 9. The results indicate that the overall Bitcoin market is not following a random walk. The daily and weekly markets are inefficient, whereas monthly data shows distinct patterns in the KS test, autocorrelation and MVR test. The reason for this behavior can be interpreted that in monthly data the information is average out and leads to remove inefficiency in monthly data.

Table 9. Summary of all tests to check the efficiency of bitcoin returns from 2013 to 2017

Series	JB test	K.S Test	ADF test	PP test	Auto-correlation	Runs Test	MVR tests
Daily	No	No	No	No	No	No	No
Weekly	No	No	No	No	No	No	No
Monthly	No	Yes	No	No	Yes	No	Yes

5. CONCLUSION

The study empirically investigates the informational efficiency in the Bitcoin market for daily, weekly and monthly returns. The main objective of this study is to test the random walk model in cryptocurrency specifically Bitcoin. Both tests Jarque-bera and KS test for normality assumption have confirmed that data is not normally distributed and rejects the hypothesis of the random walk. The stationarity in a financial time series is a condition for randomness behavior. Both ADF and PP tests report the all-time series are non-stationary. The autocorrelation is also observed in these series and the Q-Ljung box test rejects the hypothesis of no serial independence. The Runs test has also confirmed the results of the Q-Ljung box test of autocorrelation. Finally, the results of MVR have the same conclusion that the Bitcoin series are not following the random walk model. Some abnormalities are reported by the monthly data, which reflects that information is average out in the long run. These results are aligned with the previous studies that the Bitcoin market is inefficient

(Urquhart, 2016; Nadarajah & Chu, 2017; Bariviera, 2017). In an efficient market, no one can earn abnormal returns. Therefore, the results of this study have concluded that the predictability element exists in the Bitcoin market and it provides an opportunity for investors to get benefit from this inefficiency.

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