Investment in Bitcoin : A Delusion or Diligence?

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Abstract

Bitcoin investment gained great research interest, especially after the onset of the COVID-19 pandemic, a period marked by huge volatility in this asset class. This study investigated Bitcoin's persistence and hedging properties in the pre-COVID era to establish its efficiency and safety by testing relevant data. We evaluated the role of persistence in Bitcoin trading to highlight its efficiency. The GPH estimator and ARFIMA were used to map the evolving efficiency of the Bitcoin price. Our analysis of intra-day data exhibited the presence of an anti-persistence effect, following the popular conclusion of momentum and speculative trading in the Bitcoin market. The second section of this study evaluated whether Bitcoin played the role of a hedge and an asset of protection in a global portfolio manager's portfolio during extreme market volatility. Using the Threshold GARCH (TGARCH), we evaluated the trading correlation between Bitcoin prices and four major indices, namely S & P 500, FTSE, Hang Seng, and Nikkei, on daily and weekly data. We identified the time-varying hedge and safety properties of Bitcoin: volatility, speculation, less-traded history, and lack of regulatory infrastructure. Our findings added to the literature by testing the efficiency of Bitcoin in major developed economies using returns of high-frequency data, along with daily returns. We also considered extreme movements in the currency to check its hedging and protection properties in a portfolio of developed market stocks. We recommended that investors be cautious when combining this currency with different stock markets based on our findings.

Keywords : **Bitcoin, cryptocurrency, blockchain, bubble, hedge, investment**

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Any currency needs to serve three purposes, that is, it should be a medium of exchange, a unit of account, and a store of value (Bariviera, 2017; Yermack, 2013). Recent times have seen the emergence of a "synthetic" currency (Bariviera, 2017), known as the "Bitcoin." Satoshi Nakamoto (Nakamoto, 2008) coded Bitcoin for the first time. It is the first decentralized digital currency that functions as a peer-to-peer system and does not require any intermediary like a bank or a clearing house. Bitcoin has received massive attention as it is seen as an innovative investment product that is both transparent and safe. It is a sophisticated and fully decentralized payment system, implying that any central authority does not control it. A complex protocol called 'Blockchain' governs the supply of Bitcoin (Dwyer, 2015). Blockchain makes virtual currency highly secure and removes transaction costs (Kotishwar, 2020).

During the pre-2008 period, gold was seen as an inflation hedge, a diversifier, and a safe haven (Baur & Lucey, 2010) for investment. Asset classes like gold are tangible and are a store of value. However, post the financial crisis of 2008, Bitcoin emerged as an asset class offering new possibilities for diversification and risk

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management. It could also add liquidity to a portfolio while also generating high returns (Dyhrberg, 2016). The emergence of this new asset class has garnered much research attention. Plassaras (2013) and Angel and McCabe (2015) studied Bitcoin's legal, regulatory, and ethical challenges. Some studies have also studied its technical and financial aspects. Yermack (2013) observed that Bitcoin neither has an inborn worth nor does it not work with any financial exchanges to help its high market capitalization because of which it is very well regarded as a theoretical resource rather than money. Bouri, Azzi, and Dyhrberg (2017), Bouri, Molnár, Azzi, Roubaud, and Hagfors (2017), and Kristoufek (2014) found Bitcoin to be a financial asset and an investment, while Popper (2015) stated that it is digital gold. Glaser et al. (2014) found that Bitcoin lacks fundamental value that can support its high market valuation compared to other currencies and gold. They found that this digital currency is more "asset-like" than a currency. Bhattacharjee and Kaur (2015) discussed how Bitcoin evolved as a currency, the situation before and after the introduction of this currency, and its effect on the current economy.

There is a huge and increasing demand for cryptocurrencies, with the market expected to grow from \$910.3 million in 2021 to \$1902.5mn in 2028. This translates to a high CAGR of 11.1% over a 7-year period (2021–2028) (Fortune Business Insights, 2021). The primary reason for this demand is that cryptocurrency is backed by blockchain technology and thus offers an efficient, safe, fast, transparent, and decentralized system of transactions. Among the cryptocurrencies, Bitcoin is the most widely adopted digital currency, which is not only being used by various governments but also by investors and portfolio managers across the globe. The rising popularity of this asset class demands research attention, especially to understand its use in mitigating portfolio risk.

Bitcoin research was initially focused on aspects such as its operating mechanism and the related safety, regulatory, and ethical issues, however, the more recent literature has shifted focus on the aspects of volatility, trading dynamics, return and volume relationships, diversification ability, efficiency, and other financial and economic factors related to the Bitcoin market. Apart from understanding the trading and operating mechanism of Bitcoin, it is also essential to study its efficiency, its use as an investment asset, and its ability to diversify and hedge a portfolio. The test of the persistence effect has been conducted in the past primarily for stocks and currencies (Charfeddine & Ajmi, 2013). Also, with the restricted history of Bitcoin exchanging information, there are developing perspectives regarding the diversification, hedging, and a place of refuge properties of Bitcoin. The current study evaluates the market efficiency of Bitcoin in daily and intraday markets and its use as a diversification and hedging tool.

The study finds an evolving efficiency in the Bitcoin market. The overall results of our study bring out the varying hedging and protective properties of Bitcoin in the selected markets. Our findings indicate that Bitcoin investment may be considered with caution due to the variation in its liquidity, changing the regulatory regime, and volatility during periods of market distress. These findings will be useful for crypto traders in developing technical trading strategies, given the increasing persistence of new information on Bitcoin prices. They will also be of use to the portfolio managers that they can use Bitcoin as a part of short-term tactical asset allocation, given the absence of strong hedging ability.

Review of Literature

Modeling of the Persistence Effect

The persistence or long-memory effect helps establish the correlation structure of a return series and, hence, provides an insight into its predictability. Several studies have been conducted to understand this phenomenon with respect to different asset classes. Mandelbrot (1971) used rescaled range statistic (R/S statistic) to measure the persistence effect. Charfeddine and Ajmi (2013) investigated long memory in the Tunisian stock market by using FIGARCH and switching ARCH. Caporale et al. (2013) analyzed whether high-frequency traded financial time series exhibited any persistence. Pandey and Kumar (2017) analyzed how the conditional volatility of S&P CNX 500 Nifty varied in terms of its level and persistence. Krishna (2012) studied the short-term performance persistence of select Indian equity (growth) mutual funds.

Several studies conducted on the efficiency of Bitcoin (Bariviera, 2017; Caporale & Plastun, 2019; Urquhart, 2016) considered daily closing prices of Bitcoin and majorly used the R/S statistic Hurst exponent, BDS test, and fractional integration to test the persistence effect. These studies provided mixed results on Bitcoin efficiency. Bouri et al. (2019) and Caporale and Plastun (2019) found Bitcoin to lack efficiency, while Urquhart (2016) discovered efficiency in the second half of the Bitcoin returns sample. Bariviera (2017) also found similar results. The above studies, therefore, gave mixed results about the efficiency of Bitcoin. This efficiency could change over time, as it is still an evolving asset class. Various legal and regulatory changes and the introduction of other cryptocurrencies can lead to changing efficiency. This builds the case to test this cryptocurrency across various time periods. In light of the above, we test the efficiency of Bitcoin by considering both closing prices and the intra-day prices of Bitcoin in USD. The current study contributes by using the GPH estimator and ARFIMA, which are better models for establishing the persistence effect as they have less bias toward the short-term sensitivity of long memory.

Portfolio Diversification and Hedging Properties of Financial Assets

Baur and Lucey (2010) defined a hedge as "Any asset that is not related or negatively related to the other assets in the portfolio" (p. 219). These assets may not be related or negatively related to other assets during periods of stress or market turmoil. Such assets don't have any relationship with other assets when the market gives extremely low returns. These may, therefore, help in reducing losses during market turmoil or stress.

Baur and Lucey (2010) tested the hedge and safe haven properties of gold against a portfolio of stocks and bonds in extreme market conditions. Baur and McDermott (2010) found that gold acts as a hedge and a safe haven for all European markets and the United States, but the same does not apply to BRICS nations, Australia, Canada, and Japan. Bhunia and Das (2012), Do et al.(2009), Gaur and Bansal (2010), Joshi (2011), Nam et al. (2005), and Panda and Sethi (2016) also studied the role of gold as a diversifier, hedge, or safe haven. Extending the exploration of similar properties in Bitcoin, Dyhrberg (2016) used the asymmetric ARCH and TGARCH model to find that it acts as a hedge against both the stocks in the FTSE index and the US dollar. On the other hand, Bouri, Azzi, and Dyhrberg (2017) found Bitcoin to be less effective as a hedge and suitable for diversification purposes only against some major stock indices, bonds, oil, gold, dollar, and commodity index. Klabbers (2017) tested Bitcoin as an investment asset and value addition in a global market portfolio. He used the mean-variance framework along with Monte Carlo Simulation to address the estimation risk issue, which is an important aspect while evaluating a very volatile and risky asset class like Bitcoin. He concluded that there are no hedge or safe haven benefits of Bitcoin when tested in the context of a global portfolio.

Research on the hedging properties of Bitcoin has focused on the causality relationships and co-integration between Bitcoin and other asset classes like exchange rates, equity indices, oil, gold, dollar, and commodities. In qualitative terms, the relationship between Bitcoin and stock markets has also gained research attention. Though some studies have worked on the hedging properties of Bitcoin, there is a dearth of studies that quantitatively bring out these characteristics against the major stock markets. The emergence of cryptocurrencies and their large-traded volumes present an opportunity to investigate them as a hedge and a new investment opportunity during the declining equity markets. The current study picks four major indices of developed markets to examine the hedging and safety benefits of Bitcoin.

Research Methodology

Data and Econometric Modelling

The current study tests the long-run and short-run persistence effect in the Bitcoin market using daily closing and intra-day USD prices of Bitcoin. Further, following Dyhrberg (2016), we determine the hedging efficiency and protective properties of Bitcoin for global investors by relating the cryptocurrency returns with four major exchanges, that is, S&P 500, FTSE, Hang Sen, and Nikkei.

The data were sourced from Bloomberg and comprised of pre-COVID-19 daily and weekly closing prices of Bitcoin & S&P 500, FTSE, Nikkei, and Hang Seng from June 2013 until July 2019. This choice was due to the high-trade volume of Bitcoin in these markets. Along with this, time-stamped, five-minute interval data from March 16, 2010 until July 16, 2019 (approx. 25, 276 observations) were also extracted in order to understand the intra-day persistence effect in the Bitcoin market. For testing hedging efficiency, we converted Bitcoin prices to local currencies from the perspective of investment. Stata 16.0 was used to carry out all the econometric modeling as stated below.

The GPH and autoregressive fractionally integrated moving average (ARFIMA) models were used to test persistence, as defined below:

The GPH model incorporates *d*, a memory parameter, which represents X_t, a fractionally integrated process. This can be stated as:

$$(1-b)^d X_t = \in_t \qquad (1)$$

where, *b* is the backward-shift operator, error term. The error term is expected to be stationary with a mean of zero and has a continuous spectral density greater than zero. To include Fourier transformation frequencies in the model, the stated GPH test was run with power values ranging from 0.5 – 0.7. On the other hand, the ARFIMA *(p, d, q)* model lays out an asymptotically impartial perspective on long-range persistence.

An ARIMA model for any time series *st* is expressed as:

$$\rho(b)\,(1-b)^d\ s_t = \theta_{bt} \qquad (2)$$

where,

$\rho(b) = (1-\rho_{1b1}-\rho_{2b2}-\ldots\rho_{pbp})$ is an autoregressive (AR) polynomial in the lag operator L;

$bs_t = s_t - 1$;

$\theta_{bt} = (1-\theta_{1b1}-\theta_{2b2}-\ldots\theta_{pbp})$ is the moving average (MA) lag polynomial, also representing an innovation term;

d is the integer number of the differences required to make s_t stationary.

We tested the hedging capability of Bitcoin against S&P 500, FTSE, Hang Seng, and Nikkei. As a first step, following Capie et al. (2005) and Dyhrberg (2016), the Bitcoin returns were found to show ARCH effects in residuals, as a result of which, we used GARCH modeling.

Further, following Dyhrberg (2016), a Threshold GARCH (TGARCH) model was developed with mean and variance equations which take into consideration both leverage and asymmetry in returns. This model had Bitcoin returns as an independent variable and the lagged returns of Bitcoin and returns of the stock index as the dependent variables. The period under consideration was June 2013 till July 2019 (pre-COVID-19 era) to avoid disturbance of the results with volatility induced by the pandemic. Further, to test the role of Bitcoin during extreme market turmoil, following Baur and Leucy (2010), index returns were divided into quantiles, and returns in the lowest, that is, 1% and 5% quantiles, were taken as independent variable, in support of the fact that if Bitcoin returns have no or negative relationship during times when an index gives extremely low and negative returns, Bitcoin can also hedge a portfolio during these conditions and experience no crash.

Mean Equation

$$Rbitcoin_{t} = \beta_0 + \beta_1\ Rbitcoin_{t-1} + \beta_2\ Rindex_{t} + \beta_2\ Rindex_{t-i\ (q1)} + \beta_3\ \ Rindex_{t-i\ (q5)} + \in_t \qquad (3)$$

where,

$Rbitcoin_{t}$ is the current period return from Bitcoin,

$Rbitcoin_{t-1}$ is the one period lagged price of Bitcoin,

$Rindex_{t}$ is the current period return from index, i.e., S&P 500, FTSE, Hang Seng, Nikkei,

$Rindex_{t-i\ (q1)}$ and $Rindex_{t-1\ (q5)}$ are the returns of the index in 1% and 5% quantiles to account for the asymmetries of positive and negative returns.

Here, the sign of the coefficient β_2 shows the hedging capabilities of Bitcoin; whereas, the sign of the coefficient β_3 shows its properties to provide protection even during the extreme decline in the market.

Variance Equation

$$\sigma_{t2} = \alpha_0 + \alpha_{1\varepsilon 2(t-1)} + \beta\ \sigma_{2(t-1)} \qquad (4)$$

The above equation consists of an asymmetry coefficient α_1 and a leverage coefficient β.

Analysis and Results

Descriptive Statistics

Table 1 presents the descriptive statistics of Bitcoin returns and returns of all the selected indices. Table 1 shows

Table 1. *Descriptive Statistics*

	Bitcoin	Nikkei	S&P 500	FTSE	Hang Seng
Mean	0.0049	0.0005	0.0005	–0.0006	–0.0005
Median	0.0025	0.0006	0.0005	0.0005	0.0006
Maximum	0.6771	0.0771	0.0390	0.0358	0.0410
Minimum	–0.4423	–0.0792	–0.0410	–1.0000	–1.0000
Std. Dev.	0.0569	0.0132	0.0079	0.0291	0.0301
Skewness	2.0227	–0.1441	–0.5186	–31.3714	–29.0388
Kurtosis	33.30	7.75	6.07	1079.21	964.17
Jarque – Bera	49978.95	1211.95	546.02	62806327	48718518
Probability	0.0000	0.0000	0.0000	0.0000	0.0000

that the mean return of Bitcoin (0.5%) is higher than that of any of the indices selected. However, this does not qualify Bitcoin as a hedge against stock returns. Moreover, Bitcoin is riskier than the stock market, with a high deviation between the maximum and minimum values and the highest standard deviation (5.69%). The mean returns of FTSE and Hang Seng are negative, and these have an extreme negative skewness and a very high kurtosis (leptokurtic series). Overall, the returns of Bitcoin and stock indices have a non-normal distribution.

Persistence Effect

To understand the memory effect, Bitcoin data were analyzed using GPH and ARFIMA to detect long-run and short-run memory effects. First, we tested the data for the occurrence of structural breaks using the multiple breakpoints test. Table 2 shows the absence of structural breaks in the Bitcoin data. Thereafter, we studied the long-run memory effect using Bitcoin price data from 2013 – 2018. According to Kumar and Maheswaran (2012), Wang and Moore (2009), Hammoudeh and Li (2008), and Granger and Hyung (2004), the presence of spurious memory may impact results in time-series data, in order to account for this, we split the data into two halves, that is, 2013 – 2015 and 2016 – 2018.

The GPH estimate for the entire data series (Table 3) shows that the long-memory estimate *("d")* is significant at 5%, thus establishing the persistence effect. On analyzing the results for the two halves of the data series, we find d to be significant (at the 5% significance level) only for the first half of the data series. This proves that the long-memory effect is detected in Bitcoin trading between 2013 and 2015. In the case of trading data from 2016 – 2018, the long-memory effect disappeared.

The ARFIMA test presents similar results (Table 4). The test is conducted to account for fractional integration in the data series. We analyze the 5-minute intra-day trading results to detect the short-term memory effect using GPH and ARFIMA. The value of d is found to be negative and between $0 < d < 0.5$, indicating the presence of an anti-persistence effect in the intra-day returns of Bitcoin (Table 5 & Table 6).

Table 2. ***Multiple Break-Points Test***

Break Test	*F*-statistic	Scaled *F* - statistic	Critical Values
0 vs 1	5.297	5.297	8.58

Table 3. ***Geweke – Porter – Hudak Test (GPH) Results on Bitcoin Daily Returns (2013 – 2019)***

	Bitcoin Returns (2013–2019)	Bitcoin Returns (2013–2019)	Bitcoin Returns (2015–2019)
d (memory parameter)(0.5) (p - value)	–0.164645	0.3121	0.2451
	(0.189)	*(0.047)***	*(0.118)*
d (memory parameter)(0.6) (p - value)	0.29731	0.2957	0.1550
	*(0.000)****	*(0.005)***	*(0.138)*
d (memory parameter) (0.7) (p - value)	0.189071	0.1624	0.1240
	*(0.000)****	*(0.024)***	*(0.087)**

Note. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ level of significance.

Table 4. ***ARFIMA Results on Bitcoin Daily Returns : 2013 – 2018***

Bitcoin (*p*,*d*,*q*) 2013 – 2019	Constant	*Z*	*p* > *z*
ar(1)	0.1179	1.32	0.188
ma(1)	–0.4138	–3.44	0.001***
d	0.1986	3.23	0.001***
Bitcoin (*p*,*d*,*q*) 2013 – 2019	**Coefficient**	***Z***	***p* > *z***
ar(1)	0.0850	0.95	0.340
ma(1)	–0.4801	–3.77	0.000***
d	0.2516	2.89	0.004***
Bitcoin (*p*,*d*,*q*) 2015 – 2019	**Coefficient**	***Z***	***p* > *z***
ar(1)	–0.0076	–0.02	0.986
ma(1)	–0.0911	–0.20	0.845
d	0.0856	1.33	0.182

Note. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$ level of significance.

Table 5. ***Geweke – Porter – Hudak (GPH) Test Results on Bitcoin 5-Minute Returns***

d (memory parameter)(0.5) (*p* - value)	*d* (memory parameter) (0.6) (*p* - value)	*d*(memory parameter)(0.7) (*p* - value)
–0.1567	0.0445	0.0364
(0.174)	(0.550)	(0.474)

Table 6. ***ARFIMA Test Results on Bitcoin 5-Minute Returns***

Bitcoin (*p*,*d*,*q*)	Coefficient	*Z*	*p* > *z*
ar(1)	0.8786	14.12	0.000***
ma(1)	–0.8299	–9.33	0.000***
d	–0.09296	–1.53	0.125

Note. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Bitcoin as a Hedge

We analyze daily and weekly returns data to check for the presence of heteroskedasticity. Table 7 shows the absence of the ARCH effect in any of the return series, and hence, justifies the use of the TGARCH model. The results of the TGARCH model on daily returns (Table 8) indicate that Nikkei's returns in the previous period did not have any relationship with the current period's return for Bitcoin, as the coefficient (0.05833) is insignificant at the 5% level. For extreme negative returns, the coefficients are insignificant at both the 1% and 5% quantiles. The estimated coefficient is insignificant for the 5% quantile (0.217614) and insignificant as well as negative for the 1% quantile (–0.1888). This indicates that extremely low stock returns during a period did not have any effect on Bitcoin returns during the next period. The overall effect of any quantile is the sum of coefficients until that

Table 7. ***Heteroscedasticity : ARCH Test Results***

Index Daily Returns	*F* - Statistic (Daily Returns)	*F* - Statistic (Monthly Returns)
Bitcoin	124.8***	18.07***
S&P500	124.66***	5.02***
FTSE	1923231.3***	1100.89***
Nikkei	49.02***	7.15***
Hang Seng	55314.15***	3.675**

Note. ***$p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Table 8. ***TGARCH Mean Equation Between Daily Bitcoin Returns and Stock Indices***

$Rbitcoin_t = \beta0 + \beta1\ Rbitcoin_{t-1} + \beta2\ Rindex_{t-1} + \beta3\ Rindex_{t-i(q)} + \beta4\ Rindex_{t-i(q)} + \varepsilon_t$

Nikkei	Coefficient	Standard Deviation	*Z* -Statistic	Prob
β0	0.002495	0.00097	2.571655	0.0101**
β1(Bitcoin lag return)	0.004723	0.028059	0.16831	0.8663
β2(Nikkei return lag)	0.058337	0.081928	0.712054	0.4764
β3(5th quantile)	0.217614	0.271096	0.802722	0.4221
β4(1st quantile)	–0.188572	0.281473	–0.669948	0.5029
S&P 500	**Coefficient**	**Standard Deviation**	***Z*-Statistic**	**Prob**
β0	0.003294	0.001148	2.86833	0.0041***
β1(Bitcoin lag return)	–0.000668	0.029664	–0.022521	0.982
β2(S&P return lag)	–0.194963	0.163704	–1.190952	0.2337
β3(5th quantile)	–15.12498	8.415636	–1.797247	0.0723*
β4(1st quantile)	0.485329	0.253368	1.91551	0.0554*
FTSE	**Coefficient**	**Standard Deviation**	***Z*-Statistic**	**Prob**
β0	0.00354	0.001035	3.420902	0.0006***
β1(Bitcoin lag return)	0.009782	0.029117	0.335937	0.7369
β2(FTSE return lag)	–0.042863	0.125694	–0.341012	0.7331
β3(5th quantile)	11.21522	6.156149	1.821791	0.0685*
β4(1st quantile)	0.528999	0.209114	2.529719	0.0114**
Hang Seng	**Coefficient**	**Standard Deviation**	***Z*-Statistic**	**Prob**
β0	0.002068	0.001054	1.96318	0.0496**
β1(Bitcoin lag return)	0.002622	0.028451	0.092159	0.9266
β2(Hang Seng return lag)	–0.125756	0.095049	–1.323064	0.1858
β3(5th quantile)	–2.208252	4.315517	–0.511701	0.6089
β4(1st quantile)	–0.085122	0.185119	–0.459826	0.6456

Note. ***$p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Table 9. *TGARCH Mean Equation Between Weekly Bitcoin Returns and Stock Indices*

$Rbitcoin_t = \beta 0 + \beta 1\ Rbitcoin_{t-1} + \beta 2\ Rindex_{t-1} + \beta 3\ Rindex_{t-i(q)} + \beta 4\ Rindex_{t-i(q)} + \varepsilon_t$

Nikkei	Coefficient	Standard Deviation	*Z* -Statistic	Prob
β0	0.013495	0.006914	1.951912	0.0509*
β1(Bitcoin lag return)	0.048353	0.072041	0.671182	0.5021
β2(Nikkei return lag)	0.435803	0.201127	2.166807	0.0302**
β3(5th quantile)	8.006465	6.6478	1.204378	0.2284
β4(1st quantile)	0.12949	0.378493	0.34212	0.7323
S&P 500	**Coefficient**	**Standard Deviation**	***Z*-Statistic**	**Prob**
β0	0.014325	0.006637	2.158359	0.0309**
β1(Bitcoin lag return)	0.045951	0.070742	0.649552	0.516
β2(S&P return lag)	0.353761	0.431779	0.819312	0.4126
β3(5th quantile)	0.125027	1.397473	0.089466	0.9287
β4(1st quantile)	0.695022	1.537699	0.451988	0.6513
FTSE	**Coefficient**	**Standard Deviation**	***Z*-Statistic**	**Prob**
β0	0.015436	0.006913	2.232679	0.0256**
β1(Bitcoin lag return)	0.051387	0.072145	0.712276	0.4763
β2(FTSE return lag)	0.309068	0.334533	0.923878	0.3555
β3(5th quantile)	–9.190864	17.5747	–0.52296	0.601
β4(1st quantile)	0.330823	0.563791	0.586783	0.5573
Hang Seng	**Coefficient**	**Standard Deviation**	***Z*-Statistic**	**Prob**
β0	0.01496	0.007037	2.125843	0.0335**
β1(Bitcoin lag return)	0.061138	0.073636	0.830272	0.4064
β2(Hang Seng return lag)	0.439526	0.260353	1.688191	0.0914*
β3(5th quantile)	–1.301757	13.77453	–0.094505	0.9247
β4(1st quantile)	0.155979	0.397758	0.392146	0.695

Note. ***$p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

quantile. This led to a value of 0.28067 and 0.09210 at the 5% and 1% quantiles, respectively. These results of a positive insignificant coefficient for Nikkei's index returns as well as the returns at low quantiles indicate that Bitcoin acts only as a hedge but not an asset of safety during extreme market volatility in Japan. For the US, the results show a negative (–0.19) coefficient of S&P 500 returns with Bitcoin returns. The estimated coefficient is significant (at 10%) and positive for the 1% quantile (0.48532), while it is extremely negative for the 5% quantile (–15.12). The overall effect at the 5% and 1% quantiles is 15.31 and –14.83, respectively, indicating that Bitcoin is a hedge and a protective asset during extreme market movements.

For the UK, the coefficient of the overall relationship of FTSE returns with Bitcoin returns is negative and not significant (–0.04286). However, the estimated coefficient for the 1% quantile is 0.5289, and for 5%, it is 11.21, which shows a strong positive relationship at the 5% quantile. These coefficients are also highly significant. The overall effect at the 5% and 1% quantiles is 11.16 and 11.69, respectively, which indicates that Bitcoin is only a hedge during normal negative volatility but not an extreme market movement in the UK.

In the case of Hong Kong, the lagged returns of Hang Seng have a negative (–0.125) insignificant coefficient against Bitcoin returns. The estimated coefficients are negative at both the 1% quantile (–2.4162) and the 5% quantile (–2.3311). The overall effect at the 5% and 1% quantiles is –2.2082 and –0.0851, respectively, which indicates that Bitcoin is not only a hedge but also a terrific safety asset in Hong Kong.

Further, the analysis of weekly returns (Table 9) shows that the hedging benefits of Bitcoin in the Japanese markets disappeared when extended to a longer period. The coefficient of the Nikkei return is significant (0.4358). However, the coefficient of Nikkei returns for the 5th (8.0064) and 1st quantiles (0.12949) is insignificant. The overall effect of these coefficients at the 5th and 1st quantiles is 8.49055 and 8.62004, implying that in the longer term, the value of Bitcoin as a protective asset is more than as a hedge in Japan. The findings are similar for Hang Seng, where the coefficient (0.439526) is significant, but that of the 5% (–0.8010) and 1% (–0.6451) (overall coefficients) quantiles is insignificant.

The analysis of returns for S&P 500 shows an insignificant coefficient (0.3537) for S&P 500 returns and also for the 5% (0.5247) and 1% (1.2197) quantiles (overall coefficients). This indicates that Bitcoin plays the role of a hedge and an asset of protection during extreme market conditions in the US. In the case of the UK, Bitcoin is only a hedge when daily returns are analyzed. However, with weekly data, the coefficients of the FTSE index (0.3090) and that of the 5% (–8.8303) and 1% (–8.4995) quantiles (overall coefficients) are all insignificant. Hence, with a longer period of return, Bitcoin acts as a hedge and an asset of protection for UK investors.

Overall, the results indicate properties of hedge and protection during extreme volatility properties of Bitcoin in Japan, the US, and Hong Kong when daily returns are considered. However, both these properties are seen together only for the US and UK in case of weekly returns.

Discussion and Conclusion

The above analysis shows that Bitcoin is not efficient in the full sample period (2013–2018). However, the absence of the persistence effect in the second half (2016–2018) indicates that the Bitcoin market is transitioning towards efficiency. This 'better price discovery' in the Bitcoin market can be attributed to many factors, such as the increase in the number of investors, high trading activity, easy availability of information, decreasing transaction costs, and most importantly, the safety of transactions enabled by the blockchain technology. The presence of the 'anti-persistence effect' in intra-day prices (5-minute data) of Bitcoin is in line with the noisy market hypothesis (Siegel, 2006) that testifies to the existence of a 'crowd effect' in trading. Based on this, we can say that in the short - term, momentum traders dominate the market and cause price shocks, which may lead to price inefficiency. This indicates the opportunity to use trend-trading strategies to generate abnormal returns.

The presence of hedging benefits between Bitcoin and S&P 500 in the case of both daily and weekly returns shows that investors can use Bitcoin to protect their portfolios against market declines. The S&P 500 index, with a total market cap of USD 24.6 trillion (as of 30 June 2018), is an active component of a portfolio of various hedge fund managers across the globe. It is widely used for beta exposure in the US market and for several long-short strategies (for the generation of portable alpha). Hence, Bitcoin can play an important role as a risk management tool for portfolio managers among other asset classes, such as gold and commodities, as it can act as a hedge against the US equity market in daily losses and losses over a longer term.

For other markets, there is a variation in the hedging properties of Bitcoin when tested across different time horizons, that is, short term and long term. The presence of hedging benefits in the short term and its absence in the long term in Japan (Bouri, Molnár, Azzi, Roubaud, & Hagfors, 2017) and Hong Kong shows that the overall relationship between Bitcoin and these indices is inconsistent over time, and hedging benefits are short-lived. However, as markets turn bearish and the holding period increases, this consistency increases, and Bitcoin becomes more of an asset of trust during stress or extreme tail events. As seen with weekly data, Bitcoin took up both roles for the UK.

The above findings may be since Bitcoin becomes an extremely liquid asset during the market upheaval, and hence, is more volatile and speculative. However, this speculation may subside over a period of a few days, making it more reliable if any turmoil occurs in the stock market, thereby bringing out its protective properties. These findings are in line with Bouri, Molnár, Azzi, Roubaud, and Hagfors (2017), who also observed a changing relationship between Bitcoin in Japanese and other Asia-Pacific stocks. In addition, Bouoiyour and Selmi (2017) studied the fundamental, technical, and event-driven factors' impact on Bitcoin prices and found that the presence of global uncertainties caused variation in short-term and long-run returns of Bitcoin, thereby varying its reliability as a hedge. However, they also bring out the fact that a growing lack of confidence in the banking system and the fact that Bitcoin lies outside any regulatory regime of any country makes it more reliable during extreme tail events. Yermack (2013) proved a speculative trade behavior in Bitcoin, which can undermine its daily hedge property under extreme market conditions and establish the same in weekly returns, as discovered in our study for FTSE (UK). Bouri, Azzi, and Dyhrberg (2017) also supported similar findings from Bitcoin data and attributed them to the differing nature of factors driving Bitcoin prices in the short and long term. Another possible reason for the variation in hedging properties of Bitcoin may be about the period or trading history of Bitcoin. Bitcoin trading has a history of only 5 years as compared to asset classes like gold, where several decades of data are available, as used by Baur and Leucy (2010) and Capie et al. (2005). This limited history may exclude some major financial crises/shocks and make Bitcoin less established as a hedge or an asset of safety in most markets.

With a growing share of Bitcoin trading in financial markets, there is an increasing interest in studying its price behavior, diversification, and hedging benefits. However, there is still a dearth of studies in this area. The use of Bitcoin is expected to be superior to other asset classes due to its advantage of continuous trading, high encryption, and low-transactions costs.

Managerial and Theoretical Implications

The overall results of our study bring out the persistence effect as well as hedging and protective properties of Bitcoin in the US market , however, these properties are found to vary across Japan, Hong Kong, and the UK in the short and long terms. The varying results indicate that Bitcoin investment may still be considered with caution due to the variation in its liquidity, regulatory pressures, and high volatility during periods of agitation. This provides scope for investigating Bitcoin trading behavior and portfolio hedging properties as time passes and the market starts becoming more mature and also with clarity on regulations.

With a transition towards efficiency, any asset class would have better price discovery and a reduction in the possibility of beating the market. This also leads to a reduction in the possibility of arbitrage opportunities. With these improving metrics, it is possible for fund managers to include cryptocurrencies (especially Bitcoin) as part of the portfolio. This is evident with the recent listing of Bitcoin ETFs in the USA.

The presence of momentum traders in the short implies that Bitcoin may have higher volatility in the short run in comparison to the long-run trend of the price. This can lead to an opportunity for investors to use trend-based trading strategies to generate abnormal returns in the short run.

With Bitcoin showcasing some of the safe heaven properties in selected markets at selected phases, there is a possibility for Bitcoin to become another asset class in the future that has similar trading patterns as other safe-havens. However, the safe-haven property of Bitcoin can only be established with longer duration data across more markets for any asset manager to consider it as part of the portfolio to hedge the overall risk.

The study is useful for researchers and portfolio managers to understand the use of technical analysis as a trading strategy in Bitcoin along with contrarian trading, given the presence of the anti-persistence effect. These findings can be useful for technical analysts in devising technical trading strategies that can exploit inefficiency in the price movement of Bitcoin. The study also provides insights into the potential of Bitcoin as a hedge asset. This finding can be useful to portfolio managers and active investors in their strategic and tactical asset allocation decisions. It will also be useful to the policymakers, giving them a sense of direction in making Bitcoin a legal tender. This will hence allow investment for a longer term in this asset class, providing portfolio managers an additional avenue to deploy funds. The model used in the study, that is, ARFIMA, is an improvement over the R/S and GPH estimators. Additionally, using the T-GARCH model has helped to determine the spillover effect or returns and volatility versus an ordinary least square regression as used by Baur and Lucey (2010).

Overall, this study provides insights into the evolving efficiency and hedging effectiveness of Bitcoin. Cryptocurrency, in general, has the potential to emerge as a separate asset class in the future, subject to the shaping up of trading activity and the legal and regulatory infrastructure in the coming years.

Limitations of the Study and Directions for Future Research

The research on Bitcoin is still evolving as this virtual currency is new, and its behavior is still not widely established. From this perspective, our findings add more evidence to the literature on its market efficiency and portfolio diversification abilities. However, given the legal environment and new information coming into markets, and the emergence of new coins, there seems to be a limitation in establishing a concrete ground for the usage of Bitcoin as a portfolio asset. However, these results can make investors more cognizant of reliance on Bitcoin whenever distress conditions arise in the market.

Future research can investigate the efficiency of Altcoins (alternative cryptocurrencies) and the role of Bitcoin and Altcoins in hedging against other major stock markets across the globe. The study can be extended to emerging markets and to other asset classes under a dynamic framework.

Authors' Contribution

Dr. Monika Chopra conceived the idea and developed qualitative and quantitative design to undertake the empirical study. Rupish Saldi extracted research papers with high repute, filtered these based on keywords, and generated concepts and codes relevant to the study design. Dr. Monika Chopra verified the analytical methods for the study. Dr. Monika Chopra and Rupish Saldi extracted the data. The analysis was done by Dr. Monika Chopra using Stata 16.0. Both authors together wrote the manuscript.

Conflict of Interest

The authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

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