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IS CRYPTO MARKET IS A SYSTEMATIC RISK TO INDIAN STOCK MARKET? - AN EMPIRICAL ANALYSIS.

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ABSTRACT

This study attempts to examine the relationship between the Indian stock market and the crypto market. We considered one of the world's prominent stock exchanges i.e., the National Stock Exchange of India's popular index—NIFTY 50—to represent the stock market; and six major cryptocurrencies in the market such as Bitcoin, Ethereum, Tether, Cardano, Binance Coin, and Dogecoin. We have used Granger causality, Pearson correlation and multivariate regression to establish the relationship between the stock market index and the cryptocurrencies. We have also investigated whether the crypto market act as a systematic risk to the Indian stock market or not. The study has found that cryptocurrencies have a high rate of return and volatility compared to the stock market. We have also found only a very low positive correlation between the NSE NIFTY 50 and cryptocurrencies. Another relevant observation is that there is no Granger causality between the NSE NIFTY 50 and the crypto market. Finally, all the results indicates that the crypto market is not a systematic risk to Indian stock market and there is no significant relationship between Indian stock market and crypto market. Investors of Indian stock market can take decision without considering ups and downs of crypto market.

Keywords: Cryptocurrency; Bitcoin; Ethereum; Tether; NIFTY 50; Indian stock market; Granger causality.

1. Introduction

Currently, people tend to lay out money in emerging investment avenues rather than the conventional low-returns modes of investment. Cryptocurrency has become a scorching hot debate topic, drawing great attention from academicians, investors, and the business community. Recently, cryptocurrency has become an even more intriguing topic due to crypto ban and regulation by some countries as well as the news that few nations are legitimising the trade of cryptocurrencies. Cryptocurrency data show that Indians top the table of cryptocurrency traders with over 100 million investors, while the second place is held by USA with just around 27 million traders or investors.

Cryptocurrency is a digital currency based on blockchain technology and it can be used as a medium of exchange (Tschorsch & Scheuermann, 2016). Bitcoin is the first cryptocurrency, introduced by the enigmatic and pseudonymous programmer Satoshi Nakamoto in 2008 (Phillip et al., 2018). Bitcoin is considered to be the most prominent cryptocurrency due to its significant market capitalization due to which banks, hedge funds, and investment companies have become part of the crypto community (Phillip et al., 2018). With its growing popularity in India, most investors are getting attracted to Bitcoin and

other cryptocurrencies (Jani, 2018). Blau et al. (2021) observed that both economic and psychological factors affect the price of cryptocurrency to a large extent. The influence of macroeconomic factors on the price of cryptocurrencies has been evidenced (Cheng & Yen, 2020). It is also true that the cryptocurrency market is irrational and that investors respond contrarily to news regarding price levels (Aloosh & Ouzan, 2020).

The Indian stock market is an emerging stock market in the world in terms of growth. It is an unquestionable fact that there is a strong influence of macroeconomic factors in the Indian stock market (Keswani & Wadhwa, 2021). Sabalionis et al. (2021) have proved the influence of psychological factors on the price of cryptocurrency. Moreover, the market is also influenced by investors' sentiments (Das et al., 2020). The price of Bitcoin and other cryptocurrencies are highly correlated (Bouri et al., 2020). We understand from the literature that both the stock and crypto markets are impacted by economic and psychological factors. Macroeconomic variables are the main elements of systematic risk (Huong & Hoai, 2021). Since both the NIFTY 50 and cryptos are performing robustly at this time, investors are confused over the selection process. An academic examination that sheds some light on the relationship between the Indian stock market indices and the crypto markets as well as on the market performance of both will be of benefit to investors and policy makers. Hence, this study intends to find the relationship between cryptocurrencies and the NSE index (NIFTY 50). We have studied the relationship by incorporating linearity, co-movement, predictability, and return as well as the risk and volatility of stock and cryptocurrencies. Hence, it is even more important to examine the relationship between cryptocurrencies and the most prominent Indian stock market index—the NIFTY 50. Our study reveals that there is no significant relationship between crypto market and Indian stock market. Crypto market dose not act as a systematic risk to Indian stock market. The implications of this study will help Indian investors to achieve a nuanced understanding of the cryptocurrency scenarios and will support their decision-making process regarding stok market investment .

The remaining part of the paper is organized as follows. Section 2 pertains to a review of the academic literature relating to cryptocurrency and stock market. Section 3 sets out the data and research methodology of the study. Section 4 outlines results and discussion. Section 5 deals with the conclusion and policy implications.

2. Review of Literature

2.1 Cryptocurrency–influence of macroeconomic policies .

During the literature review process, we found that Professor Shaen Corbet is a major contributor of theories relating to the economic aspects of cryptocurrency. The link between macroeconomic surprises and Bitcoin returns can be explained byevaluating psychological effects on investor behaviour (Nakamoto, n.d). Corbet et al. (2020) analysed the impact of macroeconomic news on Bitcoin price fluctuations and have identified a correlation of Bitcoin prices with news relating to macroeconomic factors. In this study, Corbet and team considered macroeconomic indicators such as GDP (Gross Domestic Product), CPI (Consumer Price Index), and unemployment. Eventually, Corbet and team divulged that positive news concerning the macroeconomic indicators resulted in a positive equity return and a negative Bitcoin return and vice versa. Corbet et al. (2017) found that the international monetary policies have influenced the return of Bitcoin.

Nguyen et al. (2019) discovered that the value and volume of major cryptocurrencies are influenced by the Chinese monetary policy. The US monetary policy has no impact over the volatility of cryptocurrencies (Fama et al., 2019). Yen and Cheng (2021) examined the relationship between the economic policy uncertainty (EPU) index of China and cryptocurrency, and found a relationship between the EPU of China and the volatility of cryptocurrency. However, the EPU indices of the US, Japan, and Korea were found to have no such relationship. Shaikh (2020) has a modified opinion that global monetary policy uncertainty (MPU) and economic policy uncertainty (EPU) of the US, China, and Japan do influence the return of cryptocurrency.

2.2. Crypto market and Psychological factors.

Along with macroeconomic factors, psychological factors also influence the price of cryptocurrencies. Goczek and Skliarov (2019) reached the conclusion that popularity is the main driving factor that influences the price of Bitcoin instead of demand and supply factors. This opinion by the academic community spotlights the online interest of people in cryptocurrency as the main factor that has shaped the long-run dynamics of the crypto market. The investigation made by Kapar and Olmo (2021) came up with the result that the S&P 500 has a positive impact on the value of Bitcoin, while the fear index and gold price have a negative impact.

2.2. Influence of macroeconomic and psychological factors on Indian stock market indices

Dimic et al. (2016) found that inflation and monetary policy stance influence stock prices. Macroeconomic factors show statistically significant relationships with the stock market except for the consumer price index (Jareño & Negrut, 2016). Macroeconomic factors such as oil price and gold price influence the GCC stock price (Mensi et al., 2017). Macroeconomic factors influence the stock return volatility of the Czech Republic (Vychytilova et al., 2019). The factors that influence share returns are inflation, interest rate, currency trade, and market evolution (Geambasu et al., 2014). The Indian stock market is influenced by macroeconomic factors (Velmurugan & Janardhanan, 2016). The Bangladeshi stock market growth is highly influenced by macroeconomic factors (Mushair et al., 2020).

Along with macroeconomic factors, sentiments also influence stock prices. Sentiments and macroeconomic factors have a great impact on stock market performance (Czapkiewicz & Choczyńska, 2021). Psychological factors influence the rationality of investment decisions and thereby impact the stock price (Evbayiro-Osagie & Chijuka, 2021). Sentiments impact contemporaneous returns (Hassan Chowdhury et al., 2021). Academicians should intervene with more academic literature in terms of crypto market factors as a variable to predict the performance of Indian stock market indices.

2.3. Cryptocurrency and stock market inter-relationship

Akyildirim et al. (2020) studied the relationship between cryptocurrency returns and the volatility of stock market of the US and Europe and proved the inter-relationship of both markets. Hachicha and Hachicha (2021) are of the opinion that different international stock market indices are moving along with the cryptocurrency market. Lahiani et al. (2021) examined indices such as DAX 30, S&P 500, NASDAQ, and BSE 30 with the cryptocurrency market and found that BSE 30 had a predicting power over the cryptocurrency market. However, Gil-Alana et al. (2020) and Corbet et al. (2018) had a different opinion after their empirical research on both crypto and stock markets discovered that there is no evidence of connectedness between both the markets. Handika et al. (2019) argued that the Asian stock market does not follow the cryptocurrency market.

2.4.Indian stock market and systematic risk.

The risk inherent in the entire market or market sector is referred to as systematic risk. Systematic risk, often known as “un-diversifiable risk”, “volatility”, or “market risk”, impacts the whole market rather than simply one stock or industry. Both macroeconomic factors and psychological factors can be systematic risks as they cannot be controlled by the investors. Nandha and Hammoudeh (2007) observed that macroeconomic factors such as oil price and exchange rate are systematic risks in the Asian market. The macroeconomic factor of monetary policy is a systematic risk for the equity market (Obi et al., 2012) and the systematic risk factors are systematically priced in the equity market of the US (Choi et al., 2020).

From the past literature, it is evident that both the stock market and the cryptocurrency market have been influenced by both macroeconomic and psychological factors. We have also examined the existing theories that state the relationship between the crypto market and the stock market. We have come across several studies that show the relationship between cryptos and various stock market indices except a quality index in India. NIFTY 50 is treated as

the base index of the National Stock Exchange (NSE) in India. Also, we could not find scientific academic literature that dealt with the crypto market as a systematic risk of the Indian stock market. Hence, we have attempted to analyse the relationship between NIFTY 50 and cryptocurrencies and have tested the empirical association of the crypto market as a systematic risk of the Indian stock market. To the best of our knowledge, we could not discover any empirical study that provided insights in the research gap discussed above. The study addresses the following research questions:

a. Is the cryptocurrencies are a systematic risk to Indian stock market?

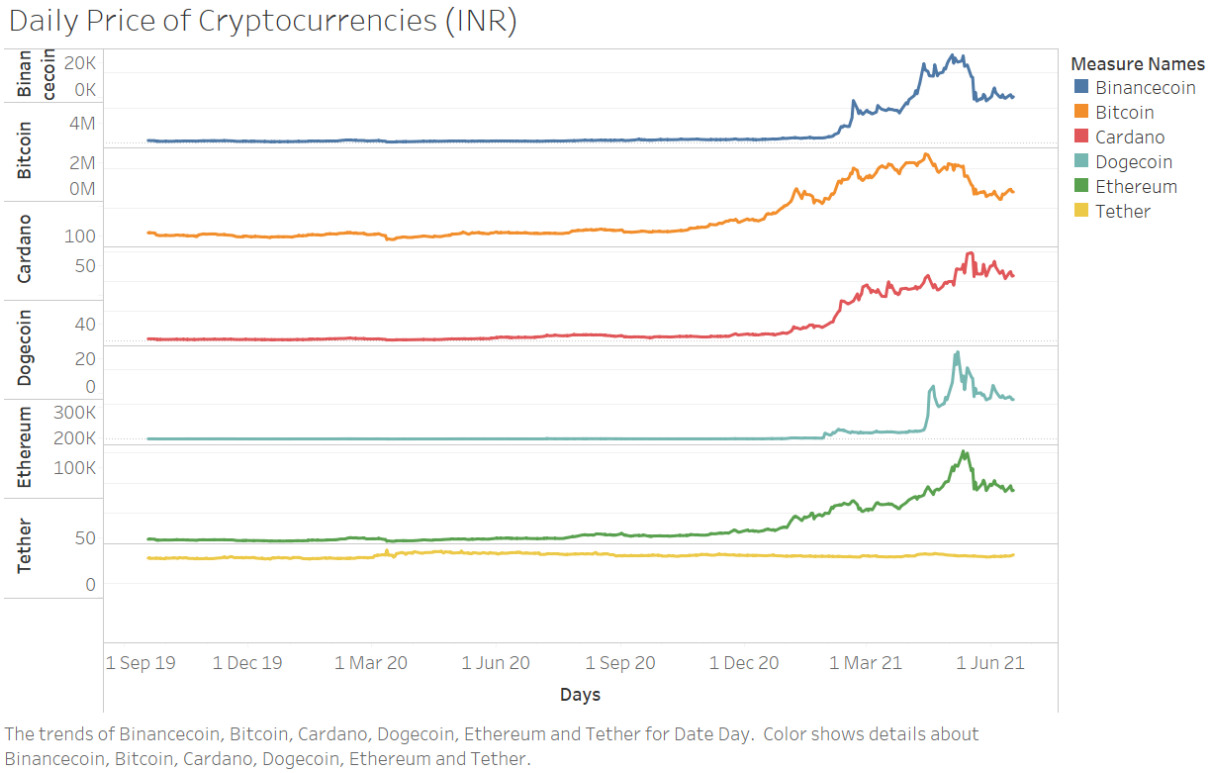
b. Is there any relationship, either positive or negative, between the Indian stock market and the cryptocurrency market?

C. How the risk return charecteristics of crypto market related with that of Indian stock market?

3. Data and Research Method

This study uses secondary data from a daily adjusted closing price of NIFTY 50, Bitcoin, Ethereum, Tether, Cardano, Binance Coin, and Dogecoin from 2019 to July 2021 from the Yahoo Finance database. The data were chosen for this research from 2019 onwards, because the cryptocurrency market in India was in the doldrums till 2019, due to which investors were reluctant to enter the crypto market until the Indian Supreme Court lifted the ban (Writ Petition (Civil) No.528 of 2018). Non-synchronicity of trading days between the stock market (NIFTY 50) and that of cryptocurrencies were adjusted by considering trading days from Monday to Friday, ignoring weekend trading days of digital currencies because the result remains unchanged (Gil-Alana et al., 2020). Data were justified on the grounds of NIFTY 50 being considered as a genuine representative of the Indian stock market. Also, we included a representation from among the most popular cryptocurrencies such as Bitcoin, Ethereum, Tether, Cardano, Binance Coin, and Dogecoin.

Figure 1: Daily Price of Cryptos



Source : Authors Calculation

Figure 2: NIFTY 50 Index Adjusted Close

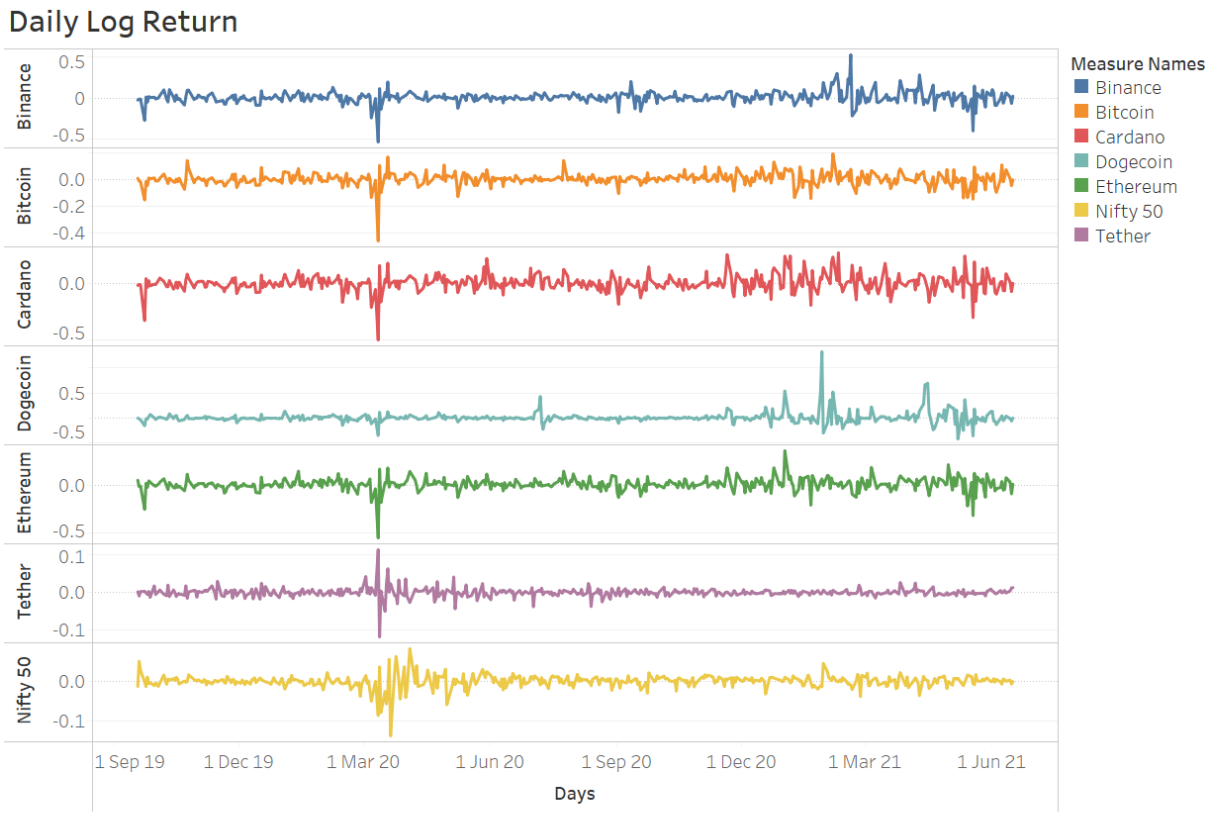
Source: Authors Calculation

The daily returns price was calculated from adjusted closing price of NIFTY 50, Bitcoin, Ethereum, Tether, Cardano, Binance Coin, and Dogecoin(See Figure 1 and 2). The study employed the natural log return method for calculating daily returns (Mahendra et al., 2021). The daily return (Rt) of all selected variables were calculated using daily adjusted closing price using natural log (ln):

$$R_{ti} = \ln(P_t/P_{t-1})$$

In this equation, R_{ti} is the daily return of price index i, P_t represents the adjusted closing value of price index at a given time t, and P_{t-1} is the value of index at the time t-1(see figure 3).

Figure 3: Daily Log Return



Source : Authors Calculation

3.1 Stationarity test

Stationarity denotes the consistency of statistical property of time series data. If the statistical characteristics of a time series do not vary over time, it means that they are stationary. There are many tests to check the stationarity of time series data. Among Unit Root Tests, the Augmented Dickey–Fuller (ADF) test was used to check the stationarity of data (Mudassir et al., 2020; Mahendra et al., 2021).

$$\Delta Yt = \beta 1 + \beta 2t + \delta \sum mi = 1 \alpha i \Delta Yt - i + \varepsilon t$$

Rejection of null hypothesis indicates stationarity of data. The test rejects the null hypothesis when the p-value is less than 0.05 and the test result has high negative ADF test statistics.

3.2 Descriptive statistics

Risk and return characteristics of NIFTY 50 and the selected cryptocurrencies were explained with the help of descriptive statistics and volatility with Box and Whiskers analysis of volatilities (Corbet et al., 2018; Sifat et al., 2019).

3.3 Pearson correlation coefficient

The correlation coefficient was used to characterize the relationship between variables in time-series data (Werner et al., 2009). To find out the characteristics of association that exists between NIFTY 50 return and the selected cryptocurrencies, the Pearson correlation coefficient was applied.

3.4 Pairwise Granger causality test:

The Granger causality test can determine the direction of causality between variables (Wei, 2018). The trend of causation for two independent variables X and Y can be calculated thus:

$$Y_t = \alpha 0 + \alpha 1 y_t - 1 + \cdots + \alpha i y t - i + \beta 1 x t - 1 + \cdots + \beta i x t - i + \varepsilon$$

$$X_t = \alpha 0 + \alpha 1 x_t - 1 + \cdots + \alpha i x t - i + \beta 1 y t - 1 + \cdots + \beta i y t - i + \varepsilon$$

Here X and Y are variables, t denotes time, and ε denotes an error. It investigates causation from X to Y and Y to X. The test can be applied to all possible pairs (X, Y) of the series. The null hypothesis is that X does not Granger cause

Y in the first regression and Y does not Granger-cause X later. Going by the methodology of previous studies, the Akaike information criterion (AIC) was used to determine the optimum lag length (Sifat et al., 2019).

3.5 Multivariete Regression:

Multivariete Regression – Multivariete regression (OLS) can be used for establishing the relationship among variables(Karp & Van Vuuren, 2017 and Suraj et al., 2020). We employed ordinary least squire (OLS) regression for analysing the the relationship between Nifty 50 and Selected cryptocurrencies. . It was done by using the following formula:

$$Y = \beta_0 + \beta_1.X_1 + \beta_2.X_2 + \beta_n.X_n\ldots.$$

In this equation, Y is the dependent variable i.e. Nifty 50, X_1 to X_n are the independent variables i.e. selected cryptocurrencies.

4. Results and Discussion

4.1 Data stationarity

Augmented Dickey–Fuller Test is done with the following hypothesis.

H_o: Time series data have a unit root, a trend, and non-stationarity.

H_1: Time series data have stationarity.

Table 1: Data Stationarity

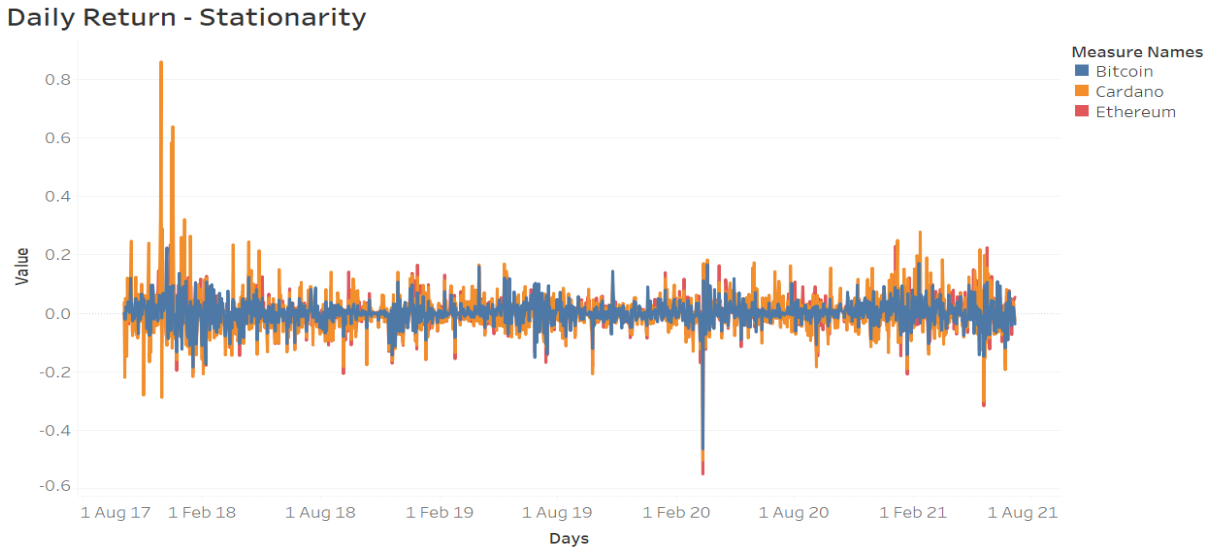
Unit Root Test—Augmented Dickey–Fuller Test			
Variable	P-value	ADF test statistics	1% si
NIFTY 50	0	-7.990963	-3.97
Bitcoin	0	-22.04282	-3.97
Ethereum	0	-13.30179	-3.97
Tether	0	-14.69928	-3.97
Cardano	0	-12.62031	-3.97
Binance Coin	0	-12.37827	-3.97
Dogecoin	0	-8.061757	-3.97

Source: Authors Calculation

Notes: Tested whether there is a trend existing in the data at level.

Table 1 reports the result of the Augmented Dickey–Fuller test. The time series data relating to NIFTY 50, Bitcoin, Ethereum, Tether, Cardano, Binance, and Dogecoin had a p-value less than 0.05 so we can reject the null hypothesis. We also found a high negative ADF test statistic and values of 1% significance level, 5% significance level, and 10% significance level, support the rejection of null hypothesis and indicates that the time series data has astationarity, meaning that there is no evidence of unit root (Miglietti et al., 2020).

Figure 4: Data Stationarity



Source : Authors Calculation

Notes: The stationarity of data is explained with the help of figure 3. All the variables plotted do not exhibit any trend, either upward or downward. The absence of a trend in time series data indicates stationarity.

4.2 Risk return characteristics of NIFTY 50 and crypto market

Descriptive statistics provides a clear picture of the return and risk characteristics of NIFTY 50 and the selected cryptocurrencies. Mean and standard deviation of daily return explains the variables' return and risk properties (Mahendra et al., 2021).

Table 2: Risk Return Characteristics—Descriptive Statistics

	NIFTY 50	Bitcoin	Ethereum	Tether	Cardano	Binance Coin	Dogecoin
Mean	0.0009	0.0032	0.0057	0.0001	0.0078	0.0065	0.0111
Median	0.002	0.0016	0.0042	-0.0002	0.0072	0.0062	-0.0007
Maximum	0.084	0.1935	0.3536	0.0569	0.2788	0.5285	1.323
Minimum	-0.139	-0.4612	-0.5472	-0.059	-0.5001	-0.5396	-0.4171
Std. Dev.	0.0168	0.0495	0.0668	0.0066	0.0772	0.0771	0.1203
Skewness	-1.6786	-1.9076	-1.3783	0.0254	-0.4902	-0.2995	4.3155
Kurtosis	18.5115	21.6708	16.8712	31.9859	9.2763	16.0396	41.9263

Source : Authors Calculation

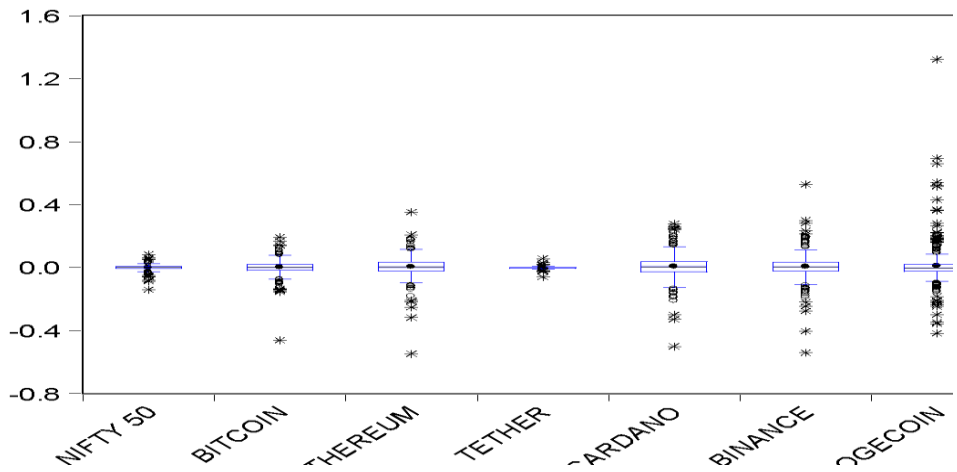
Notes: General characteristics and normality can be explained with the help of descriptive statistics.

Table 2 reports the mean and standard deviation of NIFTY 50 daily return as 0.0009 and 0.0168 respectively, which are lower than those of the selected cryptocurrencies except for Tether, which has a 0.0001 mean return, and a 0.0066 standard deviation. NIFTY 50 has low volatility because of the diversification effect. Among the selected cryptocurrencies, Tether has the lowest mean return and standard deviation, i.e., 0.0001 and 0.0066, respectively, implying lower return and risk than other cryptocurrencies and NIFTY 50. Dogecoin has the highest mean and standard deviation 0.0111 and 0.1203, respectively which signifies high returns and high risk. The most popular crypto Bitcoin has a mean return of 0.0032 and a standard deviation of 0.0495, higher than those of NIFTY 50. Ethereum has a 0.0057 mean return and 0.0668 standard deviations, higher than those of NIFTY 50, Bitcoin, and Tether. Cardano shows 0.0078 daily average returns, which is higher than that of NIFTY 50, Bitcoin, Ethereum, Tether, and Binance Coin. It also has a standard deviation of 0.0772, which is also higher than that of NIFTY 50, Bitcoin, Ethereum, and Tether, but less than that of Binance Coin and Dogecoin. Binance Coin has a mean value of 0.0065, more significant than that of NIFTY 50, Bitcoin, Ethereum, and Tether. It is riskier than NIFTY 50, Bitcoin, Ethereum, Tether, and Cardano because of the 0.0771 standard deviation.

4.3 The volatility of return

Volatility of return is a statistical measure of a stock market's return dispersion. Stock market volatility has piqued investors' interest because extreme volatility can result in significant gains or losses for investors. Bakar & Rosbi (2017) aver that volatility can be explained with the help of Kurtosis, a measure of dispersion. All the variables such as NIFTY 50 (with a Kurt of 18.5115), Bitcoin (21.6708), Ethereum (16.8712), Tether (31.9859), Cardano (9.2763), Binance Coin (16.0396), and Dogecoin (41.9263) have a positive kurtosis value of more than 3, i.e., Leptokurtic (peaked curve). The Leptokurtic value shows high volatility in all variables. Dogecoin had the highest kurtosis value of 41.9263 and can be categorized as a high-risk investment option.

Figure 5: Box and Whiskers Analysis of Volatilities



Source: Authors Calculation

Notes: Figure 4 displays all the investment avenues included in the study; we can easily understand that Dogecoin is highly volatile, while Tether is the least volatile. Also, most of the cryptocurrencies are more volatile than the Indian stock market.

4.4 Correlation of returns

The relationship between the return of NIFTY 50 and selected cryptocurrencies was examined by applying the Pearson correlation coefficient. It measures the degree to which two variables move in respect to each other in time-series data (Pollet & Wilson, 2010). Here, the Pearson correlation explains the co-movement between NIFTY 50 daily returns and the daily return of selected cryptocurrencies.

Table 3:Correlation of Return of Indian Stock Market and Return of Cryptocurrencies.

		NIFTY 50	Bitcoin	Ethereum	Tether	Cardano	Binance Coin	Dogecoin
NIFTY 50	R							
	Sig.							
Bitcoin	R	.172**						
	Sig. L	0						
Ethereum	R	.191**	.808**					
	Sig. L	0	0					
Tether	R	-.307**	-.209**	-.233**				
	Sig. L	0	0	0				
Cardano	R	.165**	.706**	.757**	-.191**			
	Sig. L	0	0	0	0			
Binance Coin	R	.128**	.692**	.684**	-.175**	.640**		
	Sig. L	0.01	0	0	0	0		
Dogecoin	R	0.01	.401**	.402**	-0.09	.386**	.271**	
	Sig.L	0.79	0	0	0.07	0	0	

Source: Authors calculation

Table 3 reports the correlation between NIFTY 50 and cryptocurrencies. Majority of the selected cryptos had a slight positive correlation with Nifty 50 and Tether had a negative correlation with the Indian stock market. Only one crypto i.e. Dogecoin doesn't correlated with Nifty 50

4.5 Pair-wise Granger causality

The pair-wise Granger causality test determines whether the return of NIFTY 50 Granger causes the return of the selected cryptocurrencies and vice versa, or if there is no relationship between these two variables(Granger, 1969). For conducting the Granger test, we had to first establish lag length criteria (Sifat et al., 2019). Going by the example of previous studies, AIC was used to determine the optimal lag length.

Table 4: Lag length criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	5794.94	NA	0.00	-27.37	-27.29915*	-27.33966*
1	5869.75	146.80	2.72e-21*	-27.48817*	-26.95	-27.28
2	5896.92	52.42	0.00	-27.38	-26.38	-26.99
3	5947.18	95.29	0.00	-27.39	-25.92	-26.81
4	5995.24	89.54	0.00	-27.39	-25.44	-26.62
5	6055.77	110.74	0.00	-27.44	-25.03	-26.49
6	6102.29	83.58	0.00	-27.43	-24.55	-26.29
7	6145.65	76.48	0.00	-27.40	-24.05	-26.08
8	6209.19	109.9512*	0.00	-27.47	-23.65	-25.96

Source: Authors Calculation

Notes: Lag length criteria test should be done in order to identify the optimum lag value for conducting Granger causality test. Done with AIC. Source: Authors' calculation.

Table 4 shows the result of lag length analysis. The cells with the '*' symbol indicate the optimal lag length for the data. Lag length analysis clearly shows that lag 1 has the lowest AIC value; therefore, the Granger causality test can be done with lag 1.

Table 5: Granger Causality

Variable	Null Hypothesis	Lags	F-Statistic	P-value
NIFTY 50, Bitcoin	Bitcoin does not Granger cause NIFTY 50	1	2.07	0.15
	NIFTY 50 does not Granger cause Bitcoin		3.21	0.07
NIFTY 50, Ethereum	Ethereum does not Granger cause NIFTY 50	1	3.54	0.06
	NIFTY 50 does not Granger cause Ethereum		2.35	0.13
NIFTY 50, Tether	Tether does not Granger cause NIFTY 50	1	2.86	0.09
	NIFTY 50 does not Granger cause Tether		1.63	0.20
NIFTY 50, Cardano	Cardano does not Granger cause NIFTY 50	1	6.42	0.01
	NIFTY 50 does not Granger cause Cardano		3.06	0.08
NIFTY 50, Binance	Binance does not Granger cause NIFTY 50	1	0.29	0.59
	NIFTY 50 does not Granger cause Binance		2.08	0.15
NIFTY 50, Dogecoin	Dogecoin does not Granger cause NIFTY 50	1	2.65	0.10
	NIFTY 50 does not Granger cause Dogecoin		1.76	0.19

Notes: This was done to analyse causality between two variables. We fail to reject the null hypothesis when the p value is more than 0.05, and vice versa. Source: Authors' calculation.

Table 5 reports the Granger causality between the return of NIFTY 50 with other variables with lag 1. The analysis reveals that NIFTY 50 and Bitcoin do not Granger cause each other as the p-value is more than 0.05. We failed to reject the null hypothesis. It supports the findings of Malladi & Dheeriya (2021) that Bitcoin does not influence the stock market and vice versa. In the case of NIFTY 50 and Ethereum, we have failed to reject the null hypothesis because its p-value is more than 0.05. It means that Ethereum does not Granger cause NIFTY 50 and NIFTY 50 does not Granger cause Ethereum. The same is the case for Tether and NIFTY 50, as the p-value is more than 0.05. So, the null hypothesis is not rejected, therefore there is no Granger cause between these two. There is an exception in NIFTY 50 and Cardano; the first null hypothesis is rejected as the p-value is less than 0.05, which means that the Cardano Granger causes NIFTY 50. However, we cannot reject the second null hypothesis of NIFTY 50 and Cardano since the p-value is more than 0.05, which means that NIFTY 50 is not a Granger cause of Cardano. As a result, Granger causality appears to act one way from Cardano to NIFTY 50 and not the other way. We cannot reject the null hypothesis in NIFTY 50 and Binance Coin because it has a p-value more than the significant level of 0.05. This means that Binance Coin has no Granger causality with NIFTY 50, and NIFTY 50 has no Granger causality with Binance Coin. As in the previous case, the p-value of the Granger causality test between NIFTY 50 and Dogecoin is more than the significance level of 0.05, which denotes that we cannot reject the null hypothesis. This, in turn, means that Dogecoin does not Granger cause NIFTY 50 and vice versa. It is clear from this analysis that there is no Granger causality between the Indian stock market and the cryptocurrencies except in the case of Cardano.

4.6 Multivariate Regression – Verifying Non- Linearity

Here we employed multivariate regression model for analysing the relationship between nifty 50 and various cryptocurrencies.

Table 6: Multivariate Regression – Establishing relationship

Dependent variable: Nifty 50

Independent Variable	Coefficient	t-Statistic	Prob.	R-squared	Adjusted R-squared	CENTERED VIF
BITCOIN	0.018797	0.657791	0.511			3.384666
ETHEREUM	0.025839	1.151995	0.25			3.798876
BINANCE	-0.009026	-0.611373	0.5413			2.192272
CARDANO	0.012034	0.74588	0.4562	0.116494	0.103992	2.623902
DOGECOIN	-0.011829	-1.662932	0.0971			1.238134
TETHER	-0.705948	-5.865395	0			1.059423

Source: Authors calculation

Note: Significance level = 0.05. VIF value should be less than 5.

From the table 6, we can understand that all the cryptos except Tether dose not had a significant relationship with the Indian stock market – Nifty 50. Tether shows a negative and statistically significant co-efficient. So we can easily draw a conclusion that cryptos are not a systematic risk to Indian stock market. We cannot build a forecasting model with these cryptos for predicting Indian stock market.

5. Major Policy Implications

Apple CEO Tim Cook suggested including cryptos in the portfolio of investors. However, on the reverse side, the opinion of Paul Krugman IMF Chief Economist opinion on the cryptos as the evil of the 21st century is

demotivating for the crypto investors. The IMF Chief Economist, Gita Gopinath afraid of the standing regulations strengths and challenges of regulation in an emerging market like India. Also, the Warran Buffet like wellknown investment giants has not been into the crypto investment so far is also noted by the investors. Rumours are saying the stock market investors may switch to the crypto market soon due to the excessive return perspective. However, this study proved the Indian stock market returns move in the same direction as those of many cryptocurrencies, but the degree is shallow. We could find that cryptocurrency has very little influence over the Indian stock market. It reveals that the return of cryptocurrency does not have any predictive power over the Indian stock market indices. The reason may be that bitcoin like cryptos are more volatile than the stock market and foreign exchange market. Moreover, the players in the cryptos are a segmented group (youngsters) who don't have the power to capture the market. Additionally, investor's sentiments and emotions are the pivot factors that determine the market price of cryptos. Crypto market is alive 24*7 days, so price trends of cryptos before the formal capital market starting time can influence the investment decision.

5. Conclusion

The study has found that cryptocurrencies have a high return and volatility rate compared to NIFTY 50. However, there is more unpredictability in the crypto market as compared to NSE indices and crypto market is subject to high volatility. Cryptocurrencies can be included in an investor's portfolio, if the investor is ready to take additional risks to attain a better return. Our relationship analysis has signified that cryptocurrency has very little influence over the Indian stock market. It reveals that the return of cryptocurrency does not have any predictive power over the Indian stock market indices. Moreover, the framework of this research observes that the Indian stock market returns move in the same direction as those of many cryptocurrencies, but the degree is shallow. It indicates that crypto currencies are not significantly related with Indian stock market and cryptos are not act as a systematic risk to Indian stock market. Investors of Indian stock market can take their decisions without looking the trends of crypto market. Supplementary analyses and additional assessments are needed to identify the influence of curiosity about of cryptocurrencies on the Indian stock market, influence of cryptos on Indian stock market after implementing taxation on Virtual Digital Assets. Further research can investigate the matter with more assessments on these grounds in due course.

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