SUNTEXT REVIEWS

SunText Review of Arts & Social Sciences

ISSN: 2766-4600

Open Access

Research Article

Volume 4:1

Determinants of Cryptocurrency: An Analysis of Volatility and Risk-Return Trade-Off

Gupta G Vaishali*

Assistant Professor, School of Management, Doon University, India

***Corresponding author:** Vaishali GG, Assistant Professor, School of Management, Doon University, Dehradun, Uttarakhand, India; E-mail: vaishali_81284@rediffmail.com

Received date: 07 April 2023; **Accepted date:** 10 April 2023; **Published date:** 18 April 2023

Citation: Vaishali GG (2023). Determinants of Cryptocurrency: An Analysis of Volatility and Risk-Return Trade-Off. SunText Rev Arts Social Sci 4(1): 153.

DOI: https://doi.org/10.51737/2766-4600.2023.053

Abstract

As an investor, volatility plays an important role in decision making. It is defined as the rate at which a security's price increases or decreases, i.e., shows pricing behaviour during a definite span of time. A high volatility will lead to high risk. Thus, it becomes critical to determine the volatility and the risk-return trade-off among investments. This paper tries to document the volatility and risk-return trade-off of four prominent crypto-currencies (Bitcoin, Ethereum, Binance and Ripple), based on market-capitalization. For analysis, closing prices of cryptocurrencies had been accumulated through secondary method for 365 days, starting from 1st March 2022 and ending on 28th February 2023. Standard Deviation and Kurtosis, used together for volatility and risk assessment, documented that Bitcoin had the highest volatility and risk associated with expected returns. Regression, for assessing the impact of volatility in BTC price on others, derived that ETH had a strong, but not very strong, bivariate relationship with BTC, among all the pairs. Durbin Watson (DW) concluded that there was no auto- correlation in the prices of crypto-currencies, i.e., previous day's price does not play significant role in today's price. For risk-return trade-off, Coefficient of Variation (CoV) had been applied. It determined that Ethereum had the highest ratio indicating its non-suitability to a conservative investor because of having the lowest returns as compared to risks involved; while Binance had the lowest Coefficient of Variation (CoV) depicting lower risk and maximum return among all.

Keywords: Volatility; Cryptocurrency; Standard deviation; Durbin watson; Bitcoin; Regression; Coefficient of variation

Introduction

Crypto-currency that has recently been in limelight, is a virtual or digital form of currency that uses block chain technology for transactions. As the name suggests, it is hidden or secret money, having no physical value [1]. It has evolved as a virtual medium of exchange platform which uses internet for transactions [2]. Since its inception, it has been fascinating for many investors, especially who are risk takers [3]. They choose crypto-currencies, over others, because of its capacity to generate high returns [4]. But, as a saying goes, every coin has two faces, same is with crypto-market. Although it has the capability to generate higher returns [5], it involves huge risks too, due to its volatile nature. As an investor, volatility plays an important role in decision making. The term volatility, in layman language, can be defined as the probability of unexpected or sudden change. Technically, it can be defined as the rate at which a security's price increases or decreases, i.e., shows pricing behaviour during a definite span of time; meaning price can vary dramatically over a short duration in either direction. The rate of volatility and risk involved are interconnected. Volatility is directly proportional to risk, i.e., a higher volatility will lead to higher risk, resulting greater probability of incurring losses. Thus, it becomes crucial to determine the dispersion of returns, i.e., to determine whether expected return is worth the volatility involved. For this purpose, there are several methods: GARCH model, beta coefficients, option pricing model, standard variations (SD), kurtosis tail risk, coefficient of variation (CoV), etc. This paper aims to document the volatility of crypto-currency. For this, four crypto-currencies have been considered, having prominent market-capitalization. These are Bitcoin (BTC), Ethereum (ETH), Binance (BNB) and Ripple (XRP). For analysis, closing prices of cryptocurrencies have been accumulated through secondary method of data collection. The data have been gathered from secondary sources such as websites: investing.com, coinmarketcap.com, published reports of IMF or OECD. Data of past one year, i.e., from 1st March 2022 to 28th February 2023, have been taken into consideration for the analysis. Objectives are the core ingredients of any study. Without these, a paper loses its direction.

Following are the research objectives of this paper.

1. To measure the volatility and risk of cryptocurrencies
2. To measure the trade-off between risk and return of cryptocurrencies
3. To determine the impact of volatility of Bitcoin prices on other cryptocurrencies

Review of Literature

Literature Gap

Many studies have been done earlier on volatility analysis and risk & return trade-off. Most of them have used GARCH model approach to measure volatility. There are very limited studies on Standard Deviation (SD) and Kurtosis, used together, to know the volatility. Also, there are many studies on risk and return performance of cryptocurrencies, but their performances have been compared with other forms of investments' performance such as gold, stocks, mutual funds, etc.

Table 1: *The following table shows the background of the related literature.*

Title	Author(s)	Data	Tools/Tests	Results
Volatility of select Crypto-currencies: A comparison of Bitcoin,Ethereum and Litecoin [6]	Jaysing Bhosaleand Sushil Mavale	Secondary data	Descriptive	In comparison with Ethereum and Litecoin, Bitcoin has more stable performance, having lowest CoV
Crypto-Currency: Trends and Determinants [7]	Dr. Debesh Bhowmik	Secondary data	Regression model, ARMA Maximum Likelihood (OPG-BHHH) model, Hamilton filter model, Wald Test	The market capitalization ofBitcoin is positively related with prices of Bitcoin and inflation rate and negativelyrelated with price of Ethereum. The market capitalization of Bitcoin has long run causality
				With the prices of Bitcoin and Ethereum and inflation rate. The volatility of market capitalization of Bitcoin showed a non-stationary process
The Challenge of Cryptocurrency in the Era of the Digital Revolution: A Review of Systematic Literature [8]	Izwan Amsyar, Ethan Christopher, Arusyi Dithi, Amar Najiv Khan and Sabda Maulana	Secondary data	Systematic Literature Review	The price of bitcoin is still very unstable and unpredictable due to their very young economy. Volatility and circulation of the bitcoin exchange rate can endanger monetary, payment and financial stability in Indonesia.

Analysis of Return and Risk of Crypto- currency Bitcoin Asset as Investment Instrument [9]	S. Dasman	Secondary data	Descriptive Analysis	Bitcoin has the highest risk and rate of return compared the others investment instruments: stock, exchange Rate and gold.
An Empirical Study of Volatility in Cryptocurrency Market [10]	Hemendra Gupta and Rashmi Chaudhary	Secondary data	GARCH model, Granger causality	A strong spillover effect among cryptocurrencies. Presence of a high volatility among the returns of the cryptocurrencies, making
				These quite a risky asset for investment.With the presence of negative news, Bitcoin and Ether's Volatility tends to increase.
Analysis of Cryptocurrency Risks and Methods of their Mitigation in Contemporary Market Conditions [11]	Elena Nadyrova	Secondary data	Scoring system based on a 100-point scale	The portfolio should include crypto as well as consist of traditional assets too. Traditional risk management method of diversification has proved its worth in empirical studies
An Investigation on the Volatility of Cryptocurrencies by means of Heterogeneous Panel Data Analysis [12]	Cansu Şarkaya İçellioğlua and Selma Önera	Secondary data	Panel data analysis	Gold prices, oil prices and S&P 500 index are directly proportional to prices of cryptocurrencies. Cryptocurrencies behave more like an investment instrument than a currency and prices of these financial assets interact with significant macro-financial indicators
Herding intensity and volatility in cryptocurrency	Pinar Evrim Mandaci and Efe Caglar Cagli	Secondary data	Granger causality test With a Fourier approximation and	During the COVID-19 Outbreak, there was a significant herding behaviour.

markets during the COVID-19 [13]			Herding intensity (Patterson and Sharma(2006) statistics)	Herding has a significant effect on market volatility, is shown by causality test
Impact of COVID-19 effective reproductive Rate on cryptocurrency [14]	Marcel C. Minutolo, Werner Kristjanpoller and Prakash Dheeriya	Secondary data	GARCH model, ADF test	The impact of the spread of COVID-19 on the price and trading volume of cryptocurrencies varies by currency and region.
Investigating the relationship between volatilities of cryptocurrencies and other financial assets [15]	Achraf Ghorbel and Ahmed Jeribi	Secondary data	BEKK-GARCH and DCC-GARCH model	BEKK-GARCH model shows higher volatility spillover between cryptocurrencies; and lower volatility spillover between cryptocurrencies and financial assets. Unlike gold, digital assets are not a haven for US investors during the coronavirus crisis
Predicting the Volatility Of Cryptocurrency Time-Series [16]	Leopoldo Catania, Stefano Grassi, and Francesco Ravazzolo	Secondary data	GARCH model, QLIKE and Score Driven–GHSKT model	Volatility predictions at different forecast horizons can be improved by more sophisticated volatility models that include leverage and time-varying skewness
Risk and Return Analysis of top Crypto Coins [17]	Lohith Papakollu	Secondary data	Descriptive Analysis, Regression, CoV	High risk in the crypto coins as compared to other asset classes. All crypto coins outperformed the stock market, derivatives & commodity markets, except Bitcoin Cash. Bright future of Bitcoin, Ethereum, Dogecoin because of the brand value as compared to others
The relationship between implied volatility and cryptocurrency Returns [18]	Akyildirim, Erdinc Corbet, Shaen Lucey, Brian Sensoy, Ahmet And Yarovaya, Larisa	Secondary data	DCC-GARCH	Investors' 'fear' plays an important role in volatility, i.e., increased fear results in increased volatility. The influence of option denoted implied volatility on the price volatility of this new financial product

Volatility co-movement between Bitcoin and Ether [19]	Paraskevi Katsiampa	Secondary data	Diagonal BEKK GARCH model and t-test	Cryptocurrencies' conditional volatility and correlation show responsiveness to major news. Ether can be seen as an effective hedge against Bitcoin
Volatility Co- Movement between Bitcoin and Stable coins: BEKK–GARCH and Copula–DCC GARCH Approaches [20]	Kuo-Shing Chen and Shen- Ho Chang	Secondary data	BEKK– GARCH and Copula–DCC GARCH Approaches	Bitcoin could co-stabilize with stablecoins. Absence of volatility spill overs across the Bitcoin and stablecoin markets. Parity deviations of the major stablecoin Tether have been slightly affected by Bitcoin volatility
Risk and return Bitcoin [21]	Isfenti Sadalia, Rico Nur Ilham, Erlina, Khaira Amalia Fachrudin, Amlys Syahputra Silalahi5	Secondary data	Tail risk	Bitcoin return distribution exhibits higher volatility than traditional G10 currencies and also stronger abnormal characteristics and heavier tails
Return and Risk Analysis on Cryptocurrency Assets [22]	Sakina Ichsani and Nugroho Satya Mahendra	Secondary data	Kruskal Wallis test and paired t-test	Kruskal Wallis test resulted that there is no risk and return comparison. Paired t-test resulted that there is a significant price difference before and after covid-19
Risk Return Performanceof	David Elferich	Secondary data	Paired t-test	Introduction of Bitcoin led to emergence of advantageous
Bitcoin and Alternative Investment Assets in Mixed Asset Portfolios in the Years 2018 to 2020 [23]				Return structures along-with significantly increased volatility.

Table 2: *Descriptive Analysis.*

	Mean	Std. Deviation	Variance	Skewness	Kurt osis

	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
BTC price	25087.1939	8621.13144	74323907.364	1.159	.128	.034	.255
ETH price	1757.2444	637.54031	406457.648	1.239	.128	.352	.255
BNB price	305.0684	55.53085	3083.675	.823	.128	.040	.255
XRP price	.456272	.1514002	.023	1.468	.128	.789	.255
BTC: Bitcoin, ETH: Ethereum, BNB: Binance, XRP: Ripple Source: Calculated through SPSS							

Table 3: *Coefficient of Variance (CoV)*

	SD	Mean	CoV (%)
BTC	8621.13144	25087.1939	34.36
ETH	637.54031	1757.2444	36.28
BNB	55.53085	305.0684	18.20
XRP	.1514002	.456272	33.18
*BTC: Bitcoin, ETH: Ethereum, BNB: Binance, XRP: Ripple Source: Calculated through Excel SD: Standard Deviation, CoV: Coefficient of Variance = (SD/Mean) *100*			

Table 4: *Regression.*

Regression Weights	R	R^2	F	p- value	DW (d)
BTC Price – ETH Price	.89	.80	1464.48	.001	2.010
BTC Price – BNB Price	.81	.67	742.03	.001	2.124
BTC Price – XRP Price	.74	.55	452.59	.001	1.957
Note: p<.05 & p<.01 BTC: Bitcoin, ETH: Ethereum, BNB: Binance, XRP: Ripple, DW: Durbin Watson Source: Calculated through SPSS					

Studies on inter-cryptocurrencies performance comparison are still smaller in number. This paper tries to fill the gap by analysing the performance of four prominent cryptocurrencies based on market-capitalization, which are Bitcoin (BTC), Ethereum (ETH), Binance (BNB) and Ripple (XRP). Along with these, this paper tries to analyse bivariate relationship of Bitcoin, being most dominant, with other selected cryptocurrencies.

Research Methodology

Secondary method has been used for collection of data on closing prices of selected crypto- currencies. The prices are in dollars ($). Daily analysis has been done, i.e., the data being collected and analysed for 365 days, starting from 1st March 2022 to 28th February 2023. For the set objectives, following tools and methods have been used: SPSS - Descriptive Analysis, Regression analysis and Durbin Watson Excel - Coefficient of Variance (CoV). Descriptive analysis (SD and Kurtosis) has been used to measure the volatility and risk involved in cryptocurrencies and similarly, Coefficient of Variation (CoV) for risk-return trade off: lower ratio, better trade-off; and Regression for impact of volatility in BTC price on others. Durbin Watson (DW) is used to predict the direction of price movement or variation (result range between 0to4) of any security. According to Rule of Thumb, if there is positive auto-correlation (DW<2), it indicates that previous day's price has a positive impact on today's price, i.e., increase in previous day's price will increase today's price and vice-versa. If the auto-correlation is negative (DW>2), increase in previous day's price will result in decline in today's price and vice-versa. No auto-correlation (DW = 0) means previous day's price does not affect today's price. But in order to test the significance level, a standard DW table is used. In this paper, the significance level for the two hypotheses was determined at .01 and .05 level.

Data Analysis and Interpretation

Standard Deviation (SD) is a statistical tool which is used to measure the volatility. It ascertains the proliferation of asset's price from its mean (average) price. While Kurtosis determines how often prices move dramatically. It is useful only when interpretated with SD. A higher SD and a lower kurtosis indicate higher volatility thus more risk involved. From Table 1, it can be observed that Bitcoin has the highest SD and a lower kurtosis, indicating highest volatility resulting in higher risk. Ethereum has high SD and high Kurtosis. Along with the risk factor, an investor would also like to determine whether expected return is worth the volatility involved. Coefficient of Variance (CoV), the ratio of standard deviation (SD) and mean, is used to determine the trade-off between the degree of risk involved and returns. The lower the ratio, the better will be the trade-off, i.e., lower CoV means favourable trade-off between risk and return. Table 2 depicts the CoV of four selected cryptocurrencies. Ethereum, followed by Bitcoin, has the highest ratio indicating its non-suitability to a conservative investor. Binance has the lowest CoV depicting lower risk and maximum return, i.e., return is approximately 5.5 times more than the risk involved, which is highest as compared to other cryptocurrencies. Ethereum has the lowest returns as compared to risks involved: 2.7 times return generating capacity.

Hypotheses

H01: There is no impact of volatility of Bitcoin prices on other cryptocurrencies
H11: There is an impact of volatility of Bitcoin prices on other cryptocurrencies
H02: There is no first-order auto-correlation
H12: There is a first-order auto-correlation
Simple linear regression (SLR), also known as Bivariate Analysis, was applied to test the null hypothesis H01 in order to know the impact of price volatility in Bitcoin (BTC) on other cryptocurrencies under consideration, i.e., Ethereum (ETH), Ripple (XRP) and Binance (BNB). The analysis was done separately, keeping independent variable (BTC price) same, and then regression was applied, first on ETH, followed by BNB and XRP. The result can be visualised in Table 3. R closer to 1 signifies a strong strength of linear relationship. The impact on prices of other cryptocurrencies, caused due to variation (volatility) in BTC price, can be explained by R2. From Table 3 it can be concluded that volatility in BTC price significantly ($p < .01$ & $p < .05$) affected the prices of other cryptocurrencies. Hence, null hypothesis (H01) was rejected and alternate hypothesis (H11) was accepted: There is an impact of volatility of Bitcoin prices on other cryptocurrencies. Durbin Watson (DW) analysis was also done to test the presence of auto-correlation (serial- correlation). Auto-correlation is used to measure relationship between current value and past values of a variable. According to Rule of Thumb, from Table 3, it can be inferred that there is no auto-correlation. But, in order to test null hypothesis H02, upper (U) and lower (L) limits, at significance level of .01 and .05, were determined through a standard DW table. If $dU < d < (4 – dU)$, then null hypothesis (H02) should be accepted, and if $d < dL$, alternate (H12) should be, accepted. From the Table 3, is can be documented that alternate hypothesis was rejected and null hypothesis was accepted at .01 and .05 significance level: There is no first-order auto- correlation [$dU < d < (4 – dU)$].

Discussion and Conclusion

The data was analysed and interpreted based on the set objectives. To measure the risk, resulting from volatility, standard deviation (SD) and kurtosis were used. Bitcoin had the highest SD and lowest kurtosis indicating maximal fluctuations in the prices and thus in returns too. In order to determine the trade-off between risk and return, Coefficient of Variance (CoV) had been used. It analysed whether it was worthy to take risk or not. Binance had the lowest risk-return ratio among others, indicating its suitability for risk-averse investors, i.e., maximum return of 5.5 times to the risk involved. Binance is then followed by XRP and BTC, while ETH has the lowest return generating capacity in comparison to risk. Simple Linear Regression was applied to test the impact of volatility in prices of Bitcoin (BTC) on other selected cryptocurrencies, which are Ethereum (ETH), Binance (BNB) and Ripple (XRP). The analysis concluded that there was an impact of price volatility on other cryptocurrencies. But while there was not a very strong bivariate relationship among the crypto-currencies, ETH had a strong bivariate relationship with BTC, among all the pairs, indicating that the two currencies have the highest market capitalization and that they have a strong bivariate relationship. The impact of volatility in BTC price on XRP price is lowest, indicating only 55% of changes in XRP can be explained by BTC price changes. Durbin Watson (DW) analysis showed no auto-correlation, i.e., there was no serial correlation. It means that there was no impact of previous day's price on today's price.

References

1. Amsyar I, Christopher E, Dithi A, Khan AN, Maulana S. The challenge of cryptocurrency in the era of the digital revolution: A Review of Systematic Literature. Aptisi Transactions on Technopreneurship (ATT). 2020; 2: 53-159.
2. Hin LH. Critical Review: Current research issues on crypto-currency and its application in financial sectors. Inter J Busi and Mgt. 2020; 15: 145.

3. Ichsani S, Mahendra NS. Return and risk analysis on cryptocurrency assets. Kontigensi: Scie J Mgt. 2022; 10:149-160.
4. Dasman S. Analysis of Return and risk of cryptocurrency bitcoin asset as investment instrument. In Acco and Finan Innova. IntechOpen. 2021.
5. Papakollu L. Risk and return analysis of top crypto coins. J Contem Issues In Busi and Govt. 2021; 27: 428-460.
6. Bhosale J, Mavale S. Volatility of select crypto-currencies: a comparison of bitcoin, ethereum and litecoin. Pune Annual Res J Symbiosis Centre for Mgt Studies, Pune. 2018; 6.
7. Bhowmik D. Crypto-Currency: Trends and Determinants. Saudi J Eco and Finance. 2022; 6: 37-50.
8. Amsyar I, Christopher E, Dithi A, Khan AN, Maulana S. The challenge of cryptocurrency in the era of the digital revolution: A Review of Systematic Literature. Aptisi Transactions on Technopreneurship (ATT). 2020; 2: 153-159.
9. Dasman S. Analysis of return and risk of cryptocurrency bitcoin asset as investment instrument. In Accou and Finance Innovations. IntechOpen. 2021.
10. Gupta H, Chaudhary R. An empirical study of volatility in cryptocurrency market. J Risk and Financial Mgt. 2022; 15: 513.
11. Nadyrova E. Analysis of cryptocurrency risks and methods of their mitigation in contemporary market conditions. Review Busin and Eco Studies. 2018; 6: 65-78.
12. Icellioglu CS, Oner S. An investigation on the volatility of cryptocurrencies by means of heterogeneous panel data analysis. Procedia Computer Science. 2019; 158: 913-920.
13. Mandaci PE, Cagli EC. Herding intensity and volatility in cryptocurrency markets during the COVID-19. Finance Res Letters. 2022; 46.
14. Minutolo MC, Kristjanpoller W, Dheeriya P. Impact of COVID-19 effective reproductive rate on cryptocurrency. Financial Innovation. 2022; 8.
15. Ghorbel A, Jeribi A. Investigating the relationship between volatilities of cryptocurrencies and other financial assets. Decisions in Eco and Finance. 2021; 44: 817-843.
16. Catania L, Grassi S, Ravazzolo F. Predicting the volatility of cryptocurrency time-series. In Mathe and Statist Methods for Actuarial Sci and Finance, MAF. 2018; 203-207.
17. Papakollu L. Risk and return analysis of top crypto coins. J Contem Issues in Business and Govt. 2021; 27: 428-460.
18. Akyildirim E, Corbet S, Lucey B, Sensoy A, Yarovaya L. The relationship between implied volatility and cryptocurrency returns. Finance Res Letters. 2020; 33.
19. Katsiampa P. Volatility co-movement between Bitcoin and Ether. Finance Res Letters. 2019; 30: 221-227.
20. Chen KS, Chang SH. Volatility Co-Movement between Bitcoin and Stablecoins: BEKK–GARCH and Copula–DCC–GARCH Approaches. Axioms. 2022; 11.
21. Sadalia I, Ilham RN, Erlina, Fachrudin KA, Silalahi AS. RISK AND RETURN BITCOIN. DLSU Business & Eco Review. 2019; 28: 8-15.
22. Ichsani S, Mahendra NS. Return and Risk Analysis on Cryptocurrency Assets. Kontigensi: Scien J Mgt. 2022; 10: 149-160.
23. Elferich D. Risk return performance of bitcoin and alternative investment assets in mixed asset portfolios in the years 2018 to 2020. SHS Web of Conferences. 2021; 129: 03006.